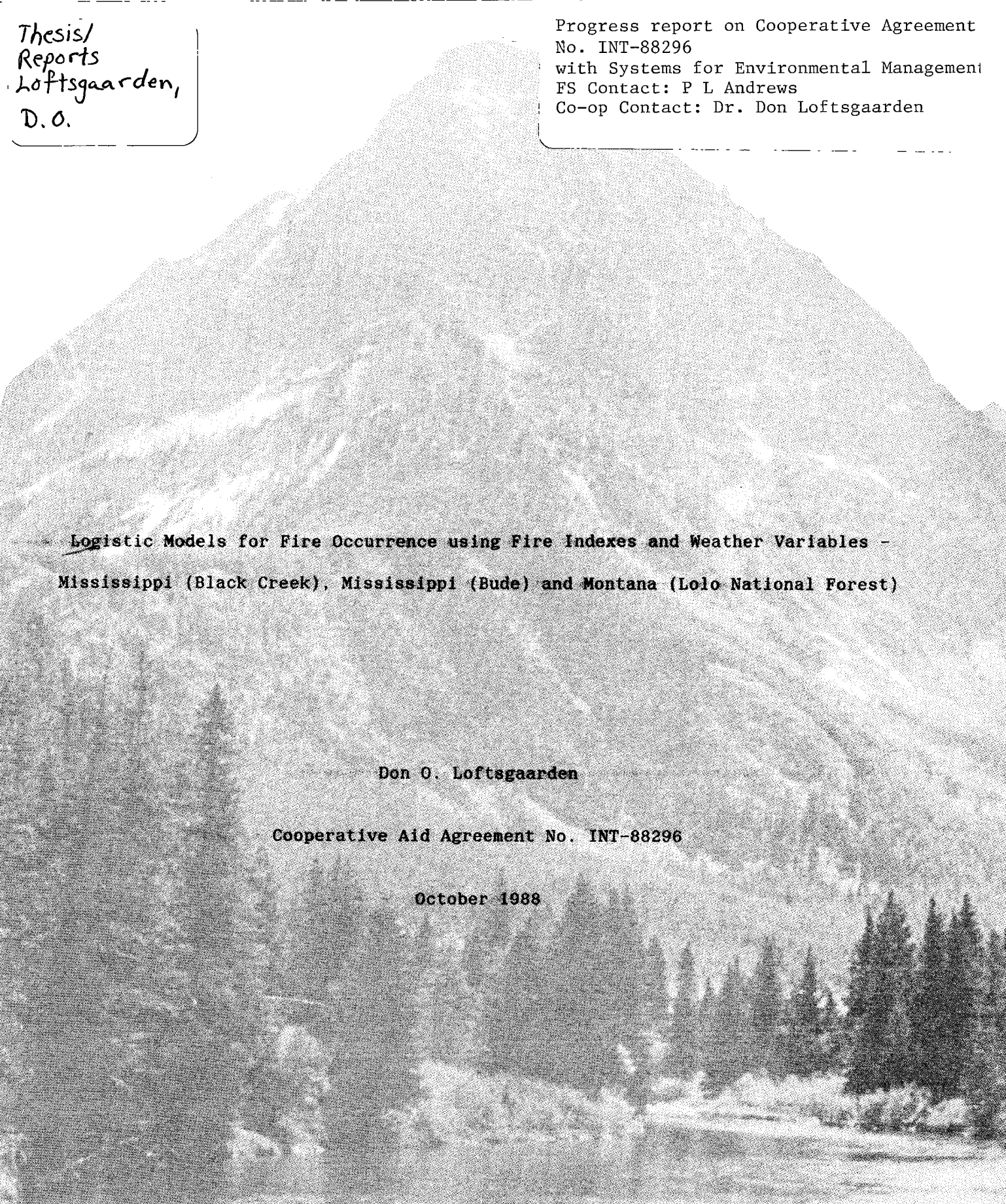
Thesis/
Reports
Loftsgaarden,
D.O.

Progress report on Cooperative Agreement
No. INT-88296
with Systems for Environmental Management
FS Contact: P L Andrews
Co-op Contact: Dr. Don Loftsgaarden



Logistic Models for Fire Occurrence using Fire Indexes and Weather Variables - Mississippi (Black Creek), Mississippi (Bude) and Montana (Lolo National Forest)

Don O. Loftsgaarden

Cooperative Aid Agreement No. INT-88296

October 1988

SYSTEMS FOR ENVIRONMENTAL MANAGEMENT

P.O. BOX 8868
MISSOULA, MONTANA 59807
PHONE: (406) 549-7478

SYSTEMS FOR ENVIRONMENTAL MANAGEMENT

A Natural Resources Research Group

Systems for Environmental Management (SEM) is a non-profit research and educational corporation based in Missoula, Montana, a regional center for natural resources agencies. Founded in 1977, SEM works cooperatively and under contract with the U.S. Forest Service, National Park Service, Bureau of Land Management, and Bureau of Indian Affairs, as well as state and academic institutions, private individuals and organizations.

SEM's diverse professional staff offers a wide range of research capabilities within the natural resources management field. The full-time staff includes specialists in fire behavior, fire history, recreation management, geography, plant ecology, forestry, meteorology, data analysis, and computer science. SEM also maintains a pool of professional affiliates that can be utilized for projects requiring additional expertise. Areas of recent research emphasis include wilderness recreation management, fire history and ecology, fire planning, and development of computerized resource management tools.

Property of
National FS Library
USDA Forest Service
240 W Prospect Rd
Fort Collins CO 80526

Logistic Models for Fire Occurrence Using Fire Indexes and Weather Variables--Mississippi (Black Creek), Mississippi (Bude), and Montana (Lolo National Forest)

Don O. Loftsgaarden

Cooperative Agreement No. INT-88296

October 1988

This report is submitted in fulfillment of section III (Par. D) of Cooperative Aid Agreement No. INT-88296 and Amendment between the Intermountain Research Station and Systems for Environmental Management, Missoula, Montana.

Table of Contents

Page no.

Chapter 1. Introduction 5

Chapter 2. Mississippi (Biloxi, Black Creek, Chickasawhay). . . . 9

THE DATA

Weather data file--description and summary statistics. . . 9
Fire data file--description and summary statistics 12
Merged data file--description and summary statistics . . . 13
Summary statistics--fire indexes, fire days, and large fire days 15
Summary statistics--weather, fire days, and large fire days 19

LOGISTIC MODELS

General discussion 22
Specific detailed examples 23
Models using fire indexes and all data 29
Models using fire indexes and Jan.-April, Oct.-Dec. . . . 31
Models using fire indexes and 10/1-12/15, 2/15-4/30 . . . 33
Models using fire indexes and cause incendiary 35
Models using weather variables and all data 38

Chapter 3. Mississippi (Bude, Homochitto) 40

THE DATA

Weather data file--description and summary statistics . . 40
Fire data file--description and summary statistics 43
Merged data file--description and summary statistics . . . 44
Summary statistics--fire indexes, fire days, and large fire days 46
Summary statistics--weather, fire days, and large fire days 51

LOGISTIC MODELS

Models using fire indexes and all data 54
Models for large firedays using fire indexes and all data 57
Models using fire indexes and selected dates 60
Models using weather variables and all data. 62
Models using weather variables and Oct-Mar 64

Page no.

Chapter 4. Lolo National Forest (all districts) 65

THE DATA

Weather data file--description and summary statistics . . 65
Fire data file--description and summary statistics 68
Merged data file--description and summary statistics . . . 70
Summary statistics--fire indexes, fire days, and large fire days 72
Summary statistics--weather variables, fire days, and large fire days 75

LOGISTIC MODELS

Models using fire indexes and all data 78
Goodness of fit--detailed examples--two methods. 79
Models based on weather variables and all data 84
Goodness of fit--detailed examples--two methods. 86

LIGHTNING CAUSED FIRES

Summary statistics--fire indexes, fire days, and large fire days 89
Summary statistics--weather, fire days, and large fire days 90
Logistic models using fire indexes 91
Logistic models using weather variables 92
Specific detailed examples including tests of fit 93

References 96

APPENDIX A. Weather and fire variables retrieved from Fort Collins Computer Center 98

APPENDIX B. Methods for evaluating logistic models 99

APPENDIX C. Programs and data files, Mississippi--Black Creek . . 106

APPENDIX D. Programs and data files, Mississippi-Bude 110

APPENDIX E. Programs and data files, Lolo National Forest 114

Chapter 1. Introduction

The overall objective of this exploratory study was to examine the relationship between National Fire Danger Rating System (NFDRS) indexes, weather variables, and fire occurrence and size. Three different locations were chosen to study:

1. Mississippi Forests
   Weather station: Black Creek (228102)
   Districts: Biloxi (02), Black Creek (03), and Chickasawhay (05).
   Years: 1974-1987

2. Mississippi Forests
   Weather station: Bude (226102)
   Districts: Bude (04) and Homochitto (08).
   Years: 1973-1987

3. Lolo National Forest in Montana
   Weather station: Missoula (241507)
   Districts: Missoula (03), Ninemile (04), Plains (05), Seeley (06), Superior (07), and Thompson Falls (08).
   Years: 1970-1985

Historical fire and weather data detailed above was taken from the National Fire Weather Data Library (NFWDL) and the National Fire Occurrence Data Library (NFODL) at the Fort Collins Computer Center (FCCC), using software developed by Larry Bradshaw. Part of this

procedure involved estimating some missing weather data, using FIRDAT to compute NFDRS indexes for each day and preparing the fire and weather data for merging into a single data file. This is discussed further later in the report.

SAS programs were developed to carry out the analyses reported here. Similar work was carried out on the Lolo National Forest (Loftsgaarden 1987) using SPSSX programs. When the Intermountain Fire Sciences Laboratory switched from the Perkin-Elmer to the Data General computer, SAS was available and SPSSX was not, necessitating the conversion to SAS programs.

A fire day is a day on which one or more fires were discovered in the area being studied. The main thrust of this study was the development of logistic regression models for the probability of a fire day as a function of one or more NFDRS indexes or one or more weather variables. Because there are many predictor variables, a large number of models can easily be generated. In addition, each choice of a fuel model results in all new values for the NFDRS indexes and hence more predictor variables. There are 20 possible fuel models.

Fire in the preceding paragraph is used in a generic sense. Fire can mean any fire, a large fire, a lightning-caused fire, an incendiary-caused fire, etc., with the corresponding modification in the definition of a fire day. Each time one changes the definition of a fire day, a whole new set of logistic models can be constructed for the probability of a fire day as discussed above.

A major need is a way of quickly comparing competing models and choosing the "best" models. From one point of view, this means tests of fit for logistic models. Much effort was spent on this problem during

the course of this study with only partial success. Tests of fit for logistic models is a very active area of research in statistics at the moment. The problems are difficult but steady progress towards their solutions is being made. Three ways of comparing logistic models are discussed in this report. An approach using average scores was discussed in an earlier study (Loftsgaarden 1987). On the basis of work done in this study, that approach has been found unacceptable.

The problem of choosing between logistic models is important in this research. Techniques developed will be used to decide which fuel model is best for a particular area. They can also be used to study effects of changes made in NFDRS models. It is unfortunate that a simple easy solution is not available as yet.

Chapter 2 contains the analysis of data for the Black Creek weather station and corresponding districts. These forests had a substantial number of fires--about 1 percent were lightning-caused with incendiary listed as the cause in 76 percent of the fires. For this data set, logistic models based on NFDRS indexes for fuel models C and D were constructed using (1) all fires, (2) only fires during the fire season 2/15-4/30 and 10/1-12/15, (3) fires in months when most fires occurred 10/1-12/31, 1/1-4/30, and (4) fires with cause listed as incendiary. Logistic models based on weather variables and all data were also constructed.

Chapter 3 contains the analysis of data for the Bude weather station and corresponding districts. This data set had very few fires. The cause of fire was listed as lightning in 1.5 percent of the fires and incendiary in 55 percent of the fires. Logistic models based on NFDRS indexes and fuel models C, D, and G were constructed. A few

logistic models were constructed using data from selected periods of time--(a) during the fire season (10/1-12/15, 2/15-4/30), (b) during the period before greenup (11/1-4/30), and (c) during months when most fires occurred (10/1-3/31). Logistic models based on weather variables using all data and using data for the months (October-March) were constructed. A few logistic models for large fire days, based on NFDRS indexes, were also constructed.

Chapter 4 contains the analysis of data for Lolo National Forest. This data set contains a substantial number of fires. The cause is listed as lightning for 69 percent of these fires while incendiary is listed as the cause in only 1.1 percent of these fires. Logistic models for fire day and all data were constructed using NFDRS indexes based on fuel models C and G as well as the weather variables. Logistic models for lightning-caused fires based on fire indexes and weather variables were also constructed.

In Chapters 2, 3, and 4, a large amount of statistical information is summarized in descriptive form concerning fires, fire indexes, and weather variables. Much information about the relationship between fire days and fire indexes or weather variables is also summarized.

In an earlier report (Loftsgaarden 1987), logistic models for the probability of a fire day were used to construct Poisson models for the probability of 0, 1, 2, 3 . . . fires for a day. These same techniques can be used with the logistic models constructed here. These techniques are not illustrated in this report.

Chapter 2. Mississippi

Districts: Biloxi (02), Black Creek (03), Chickasawhay (05)

Weather Station: Black Creek (228102)

THE DATA

Data used were from the three districts that use the Black Creek Weather Station (228102) in Mississippi. The districts used were Biloxi (02), Black Creek (03), and Chickasawhay (05). Years studied were 1974-1987 although there were no weather data available in 1986 and also substantial portions of 3 or 4 other years had no weather data.

WEATHER DATA FILE

Weather data were retrieved from the National Fire Weather Data Library. Variables retrieved are listed in Appendix A. The Black Creek Weather Station operated year-round. After the data were retrieved, NFDRS indexes were computed for each day using FIRDAT for one or more fuel models. Fuel models used in this part of the study were C and D. Occasionally, several days in a row had missing weather information. This missing weather information was estimated and filled in, using linear interpolation. In this study, however, days that were in a string of 8 or more missing weather days were not used. Some summary statistics follow:

Missing days	0	1	2	3	4	5	6	7	
Frequency (days)	3601	68	14	6	12	5	6	7	3719
Number of instances	3601	68	7	2	3	1	1	1	

Year	74	75	76	77	78	79	80	81	82	83
Days of useable weather	365	180	180	355	293	276	306	365	355	345

84	85	86	87	
366	160	0	165	3719

Month	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep
Days of useable weather	331	282	331	351	299	270	302	279	300

Oct	Nov	Dec	
304	330	340	3719

Summary Statistics on Weather Variables and Fire Indexes

N=3719

Variable	Mean	Minimum	Maximum	Standard deviation
Temperature	74.8	20	103	13.8
Relative humidity	56.6	5	100	19.2
Windspeed	1.7	0	7	1.2
Maximum temperature	78.7	25	105	12.6
Minimum temperature	55.7	3	32	14.6
Maximum humidity	99.6	42	100	3.8
Minimum humidity	45.8	1	100	16.6
Precipitation time (hours)	1.3	0	24	3.0
Precipitation amount	19.6	0	971	60.4
1-hour fuel moisture	10.4	2	33	5.2
10-hour fuel moisture	14.8	2	63	9.0
100-hour fuel moisture	18.4	12	36	2.6
1000-hour fuel moisture	21.8	16	35	3.3
Woody moisture	123	70	200	45.2
Herbaceous moisture	95.3	2	250	72.5
Fuel Model C				
IC	7.2	0	64	8.9
SC	3.2	0	32	4.6
ERC	4.9	0	24	4.2
BI	9.2	0	54	9.7
FLI	6.9	0	38	6.9
Fuel Model D				
IC	9.1	0	62	8.8
SC	8.9	0	62	9.8
ERC	22.3	0	61	13.4
BI	31.6	0	122	24.2
FLI	23.4	0	87	16.9

FIRE DATA

Data for fires for the Mississippi districts of Biloxi, Black Creek, and Chickasawhay were retrieved from the National Fire Occurrence Data Library. This file had one case for each fire in each district for years 1974-1987. A case was added to this file for each day in each district that did not have a fire. A list of variables taken from the NFODL is given in Appendix A. Summary information on the fires on days with useable weather data follow:

District	Number of Fires
Biloxi	544
Black Creek	1105
Chickasawhay	301
	1950

Size	Number of fires
0 - .25 acres	206
.26 - 9 acres	1203
10 - 99 acres	502
100 - 299 acres	27
300 - 999 acres	6
1000 - 4999 acres	6
	1950

Year	74	75*	76*	77	78	79	80	81	82	83
Number of fires	104	102	138	145	177	108	175	324	149	131

84	85	86	87	
173	123*	0**	101*	1950

*Years where weather information was missing for approximately half of the days.

**No weather data available.

Discovery month	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	
Number of fires	298	337	432	145	62	103	69	17	18	125	150	194	1950

Discovery day of week	Number of fires
Sunday	314
Monday	242
Tuesday	240
Wednesday	289
Thursday	235
Friday	258
Saturday	372
	1950

Cause	Number of fires
Lightning	20
Equipment use	42
Smoking	23
Campfire	17
Debris burning	84
Railroad	1
Incendiary	1485
Children	3
Miscellaneous	275
	1950

MERGED DATA FILE

The weather and the fire data files were merged. Weather data and fire indexes were attached to each case in the fire data file. Cases in the fire data file with no weather/fire index data were deleted. At this point many days have several cases (one for each fire that day). The cases for each day are collapsed to one case with number of fires and number of large fires on a day computed and added to the case for each day. Note that this merged data file was constructed using fires from all three districts.

Number of Days with K Fires

Number of fires (K)	0	1	2	3	4	5	6	7	8	9	10	≥11	
Number of days with K fires	2794	496	190	104	49	33	21	13	7	5	3	4	3719

Number of Days with K Large Fires*

Number of large fires (K)	0	1	2	3	4	5	6	7	
Number of days with K large fires	3319	305	71	13	5	2	3	1	3719

* Large fire - 10 acres or larger

The next table illustrates the type of breakdown that is easily available for any of the variables.

Number of Days with K Fires by ERC (D)

No. of fires	0	1	2	3	4	5	6	7	≥8	Total
ERC(D)										
0-6	324	11	4	2	0	0	1	0	0	342
7-12	372	24	8	6	0	0	2	0	0	412
13-15	545	57	17	7	2	2	0	2	0	632
16-19	578	94	22	9	5	4	1	1	2	716
20-28	419	54	21	8	6	1	2	0	2	513
29-37	249	71	32	18	9	7	2	0	3	391
38-43	159	88	40	19	12	12	8	5	6	349
44-50	105	82	42	30	12	4	3	5	5	288
51-61	43	15	4	5	3	3	2	0	1	76
	2794	496	190	104	49	33	21	13	19	3719

The next several tables give summary information about the NFDRS fire indexes ERC, BI, IC, SC, FLI for fuel models C and D, fire days and large fire days for all fires. Similar information is given for ERC and BI for fuel model D and only fires with cause incendiary.

Summary statistics relating fire indexes, firedays[1] and large firedays[2]

ERC1(C)[3]	Days	Firedays		Large firedays		ERC2(D)[4]	Days	Firedays		Large firedays	
0	534	39	.073	17	.032	0-6	342	18	.053	8	.023
1-2	622	95	.153	39	.063	7-12	412	40	.097	21	.051
3	516	76	.147	28	.054	13-15	632	87	.138	36	.057
4	501	90	.180	35	.070	16-19	716	138	.193	43	.060
5-6	598	123	.206	54	.090	20-28	513	94	.183	38	.074
7-9	392	179	.457	81	.207	29-37	391	142	.363	69	.177
10-14	434	266	.613	127	.293	38-43	349	190	.544	89	.255
15-18	103	47	.456	15	.146	44-50	288	183	.635	85	.295
19-24	19	10	.526	4	.211	51-61	76	33	.434	11	.145
	3719	925		400			3719	925		400	

BI1(C)	Days	Firedays		Large firedays		BI2(D)	Days	Firedays		Large firedays	
0	485	35	.072	15	.031	0	179	14	.078	4	.022
1-2	223	20	.090	7	.031	1-10	244	10	.041	5	.021
3	537	75	.140	29	.054	11-14	572	60	.105	25	.044
4	664	116	.175	43	.065	15-18	726	119	.164	40	.055
5-6	519	87	.168	33	.064	19-24	434	70	.161	26	.060
7-16	373	98	.263	42	.113	25-40	366	83	.227	38	.104
17-21	345	167	.484	78	.226	41-58	486	183	.377	79	.163
22-28	361	204	.565	100	.277	59-69	350	184	.526	90	.257
29-35	159	91	.572	36	.226	70-80	220	116	.527	48	.218
36-40	38	25	.658	15	.395	81-92	104	60	.577	32	.308
41-54	15	7	.467	2	.133	93-122	38	26	.684	13	.342
	3719	925		400			3719	925		400	

[1] Day with at least one fire discovered
[2] Day with at least one fire 10 acres or larger discovered
[3] Fuel model C
[4] Fuel model D

IC1(C)	Days	Firedays		Large firedays	
0	725	55	.076	23	.032
1-2	561	78	.139	35	.062
3	459	73	.159	23	.050
4-5	596	100	.168	37	.062
6-9	422	117	.277	46	.109
10-15	392	183	.467	93	.237
16-25	353	197	.558	89	.252
26-35	146	85	.582	40	.274
36-48	59	34	.576	13	.220
49-64	6	3	.500	1	.167
	3719	925		400	

IC2(D)	Days	Firedays		Large firedays	
0	514	36	.070	14	.027
1-3	517	58	.112	31	.060
4-6	869	129	.148	43	.050
7-9	498	111	.223	45	.090
10-13	454	155	.341	68	.150
14-17	293	118	.403	61	.208
18-27	389	210	.540	90	.231
28-35	116	73	.629	36	.310
36-42	49	26	.531	9	.184
43-62	20	9	.450	3	.150
	3719	925		400	

SC1(C)	Days	Firedays		Large firedays	
0	1345	144	.107	52	.039
1	1046	183	.175	70	.067
2-5	417	145	.348	64	.154
6-9	487	225	.462	103	.212
10-13	254	132	.520	66	.260
14-20	144	78	.542	36	.250
21-32	26	18	.692	9	.346
	3719	925		400	

SC2(D)	Days	Firedays		Large firedays	
0-1	414	31	.075	12	.029
2	825	101	.122	35	.042
3	518	80	.154	31	.060
4-6	518	92	.178	36	.070
7-12	404	130	.322	56	.139
13-18	433	189	.437	83	.192
19-25	300	147	.490	73	.243
26-32	194	95	.490	42	.217
33-42	83	41	.494	22	.265
43-50	21	14	.667	7	.333
51-62	9	5	.556	3	.333
	3719	925		400	

FLI1(C)	Days	Firedays		Large firedays		FLI2(D)	Days	Firedays		Large firedays	
0	359	23	.064	12	.033	0-8	377	18	.048	8	.021
1	231	20	.087	7	.030	9-10	506	55	.109	23	.046
2	547	76	.139	29	.053	11-12	588	95	.162	34	.058
3	692	116	.168	43	.062	13-15	445	68	.153	25	.056
4	524	87	.166	33	.063	16-24	434	85	.196	34	.078
5-10	283	59	.209	26	.092	25-37	398	124	.312	52	.131
11-14	408	169	.414	75	.184	38-46	477	217	.455	102	.214
15-20	452	250	.533	122	.270	47-54	282	148	.525	68	.241
21-26	195	108	.554	46	.236	55-62	156	82	.526	38	.244
27-30	22	15	.682	6	.273	63-70	42	23	.548	12	.286
31-38	6	2	.333	1	.167	71-80	13	10	.769	4	.308
	3719	925		400		81-100	1	0	.000	0	.000
							3719	925		400	

Summary Statistics Relating Fire Indexes, Firedays, and Large Firedays

(Only fires with cause incendiary)

ERC2(D)	Days	Firedays		Large firedays		BI2(D)	Days	Firedays		Large firedays	
0-6	342	16	.047	8	.023	0	179	12	.067	4	.022
7-12	412	30	.073	16	.039	1-10	244	7	.029	4	.016
13-15	632	53	.084	22	.035	11-14	572	35	.061	16	.028
16-19	716	76	.106	22	.031	15-18	726	64	.088	23	.032
20-28	513	66	.129	23	.045	19-24	434	44	.101	12	.028
29-37	391	131	.335	60	.154	25-40	366	57	.156	23	.063
38-43	349	170	.487	80	.229	41-58	486	161	.331	65	.134
44-50	288	155	.538	71	.247	59-69	350	163	.466	79	.226
51-61	76	27	.355	7	.092	70-80	220	103	.468	43	.196
	3719	724		309		81-92	104	53	.510	29	.279
						93-122	38	25	.658	11	.290
							3719	724		309	

Summary Statistics Relating Weather Variables, Firedays and Large Firedays

RELHUMID	Days	Firedays		Large firedays	
5-20	66	39	.591	11	.167
21-30	275	141	.513	52	.189
31-42	575	189	.329	79	.137
43-50	575	150	.261	70	.122
51-58	566	138	.244	70	.124
59-67	539	122	.226	55	.102
68-76	570	99	.174	46	.081
77-86	297	32	.108	12	.040
87-100	256	15	.059	5	.020
	3719	925		400	

HUMRISK	Days	Firedays		Large firedays	
1	2631	675	.257	312	.119
2	1088	250	.230	88	.081
	3719	925		400	

PRECTIME	Days	Firedays		Large firedays	
0	2630	804	.306	349	.133
1	324	56	.173	24	.074
2	205	23	.112	6	.029
3	109	10	.092	6	.055
4	91	6	.066	5	.055
5-6	107	7	.065	3	.028
7-8	135	11	.082	5	.037
9-11	45	3	.067	0	.000
12-15	37	3	.081	1	.027
16-24	36	2	.056	1	.028
	3719	925		400	

PRECAMT	Days	Firedays		Large firedays	
0	2713	817	.301	358	.132
1-7	162	37	.228	10	.062
8-20	177	20	.113	6	.034
21-34	110	15	.136	7	.064
35-50	137	7	.051	4	.029
51-75	125	9	.072	7	.056
76-114	111	11	.099	4	.036
115-156	55	1	.018	0	.000
157-218	56	6	.107	3	.054
219-510	64	2	.031	1	.016
511-971	9	0	.000	0	.000
	3719	925		400	

FUELMOI1*	Days	Firedays		Large firedays	
2-5	335	137	.409	47	.140
6	339	131	.386	55	.162
7	399	119	.298	54	.135
8	489	143	.292	65	.133
9	510	124	.243	51	.100
10	425	107	.252	51	.120
11-12	465	94	.202	44	.095
13-15	290	40	.138	22	.076
16-20	224	16	.071	6	.027
21-27	193	11	.057	5	.026
28-33	50	3	.060	0	.000
	3719	925		400	

FUELMOI2	Days	Firedays		Large firedays	
2-5	175	35	.200	13	.074
6-9	903	225	.249	91	.101
10-11	505	167	.331	75	.149
12-13	589	186	.316	80	.136
14-16	542	179	.330	79	.146
17-21	393	75	.191	36	.092
22-25	277	30	.108	13	.047
26-33	187	13	.070	7	.037
34-49	73	11	.151	5	.069
50-63	75	4	.053	1	.013
	3719	925		400	

FUELMOI3	Days	Firedays		Large firedays	
12-15	132	56	.424	24	.182
16	414	90	.217	35	.085
17	682	170	.249	76	.111
18	653	211	.323	110	.169
19	660	217	.329	88	.133
20	423	86	.203	34	.080
21-22	427	71	.166	25	.059
23-24	180	17	.094	4	.022
25-36	148	7	.047	4	.027
	3719	925		400	

FUELMOI4	Days	Firedays		Large firedays	
16-17	157	58	.369	21	.134
18	431	66	.153	26	.060
19	545	129	.237	58	.106
20	414	82	.198	34	.082
21	364	103	.283	54	.148
22	409	95	.232	37	.091
23	351	98	.279	47	.134
24	296	97	.328	38	.128
25-26	399	110	.276	49	.123
27-28	207	58	.280	28	.135
29-30	94	21	.223	5	.053
31-35	52	8	.154	3	.058
	3719	925		400	

*FUELMOI1, FUELMOI2, FUELMOI3, FUELMOI4 are the 1-hr, 10-hr, 100-hr, and 1000-hr fuel moistures, respectively.

TEMP	Days	Firedays		Large firedays	
20-50	234	71	.303	31	.133
51-55	166	50	.301	17	.102
56-63	367	142	.387	67	.183
64-68	337	112	.332	50	.148
69-74	539	176	.327	78	.145
75-80	605	147	.243	75	.124
81-86	603	122	.202	41	.068
87-92	644	65	.101	22	.034
93-96	197	34	.173	17	.086
97-103	27	6	.222	2	.074
	3719	925		400	

MAXTEMP	Days	Firedays		Large firedays	
25-51	115	33	.287	16	.139
52-62	327	120	.367	49	.150
63-70	489	176	.360	76	.155
71-76	531	179	.337	81	.153
77-82	626	178	.284	86	.137
83-87	499	99	.198	39	.078
88-91	495	61	.123	24	.049
92-93	274	29	.106	11	.040
94-95	197	22	.112	5	.025
96-98	141	18	.128	9	.064
99-105	25	10	.400	4	.160
	3719	925		400	

MOISHERB	Days	Firedays		Large firedays	
2-6	303	181	.597	72	.238
7-9	425	221	.520	106	.249
10-16	481	158	.329	79	.164
17-30	201	22	.110	8	.040
31-105	79	15	.190	11	.139
106-120	381	89	.234	33	.087
121-135	559	88	.157	35	.063
136-149	373	50	.134	17	.046
150-160	372	48	.129	21	.057
161-180	168	21	.125	5	.030
181-200	131	9	.069	4	.031
201-220	102	15	.147	7	.069
221-240	65	2	.031	1	.015
241-250	79	6	.076	1	.013
	3719	925		400	

MOISWOOD	Days	Firedays		Large firedays	
70	1418	580	.409	264	.186
71-100	36	6	.167	4	.111
101-120	30	12	.400	7	.233
121-140	484	103	.213	39	.081
141-150	580	110	.190	45	.078
151-160	353	42	.119	13	.037
161-175	351	30	.086	10	.029
176-190	233	26	.112	11	.047
191-200	234	16	.068	7	.030
	3719	925		400	

LOGISTIC MODELS (General Discussion)

One main objective of this study was to investigate the use of logistic models to obtain estimates for the probability of a fire day as a function of one or more NFDRS indexes or weather variables. A very brief general discussion of logistic models in this setting is given here.

For each day we consider an indicator random variable Y where Y is 0 if there is no fire and 1 if there is one or more fires. The probability function for Y is

y	0	1
P(Y=y)	1-P	P

where P = the probability of a fire that day.

Note that $E(Y) = P$. Often one assumes that $E(Y) = \alpha + \beta \cdot x$. Here we assume that

$$P = E(Y) = \frac{e^{\beta_0 + \beta_1 \cdot x}}{1 + e^{\beta_0 + \beta_1 \cdot x}} = \frac{1}{1 + e^{-\beta_0 - \beta_1 x}} = \frac{1}{1 + e^{\beta_0' + \beta_1' x}}$$

where x is an NFDRS index or perhaps a weather variable.

When P is plotted against x, one obtains the well known logistic curve. It is bounded below and above by 0 and 1 which is appropriate since P is a probability. A specific example of such a curve may be found a few pages ahead in this report. We note in passing that

$$P' = \ln \left(\frac{P}{1-P} \right) = \beta_0 + \beta_1 \cdot x$$

This is called the logit transformation and it is often used to check on the validity of the logistic model geometrically.

The data for n days are given by $(x_1, y_1), (x_2, y_2), \ldots (x_n, y_n)$ where x_i = index value on day i and y_i is 0 or 1 depending on whether there is a fire that day or not. These raw observations can be used to obtain maximum likelihood estimators b_0 and b_1, for β_0 and β_1. A second method of using these data is to group the observations using non-overlapping intervals for the index variable. One then uses the number observations and number of fire days within each interval as the raw data. The procedure CATMOD in SAS was used to get the maximum likelihood estimates b_0 and b_1 for β_0 and β_1. Most models were constructed using the original observations and a few were constructed using grouped data. Some models were constructed using both methods. There was very little difference in the models obtained using either method.

The logistic model, $\hat{P}$, for P has the following form:

$$\hat{P} = \frac{e^{b_0 + b_1 x}}{1 + e^{b_0 + b_1 x}} = \frac{1}{1 + e^{-b_0 - b_1 x}} = \frac{1}{1 + e^{b_0' + b_1' X}} .$$

$\hat{P}$ is the estimated probability of a fire day as a function of x.

Logistic models with two or more index variables in them are easily constructed. With two index variables, the form of the logistic equation would be

$$\hat{P} = \frac{e^{b_0 + b_1 x_1 + b_2 x_2}}{1 + e^{b_0 + b_1 x_1 + b_2 x_2}} .$$

Example

As an example, we consider a logistic model developed using the index ERC(D), the ERC index based on fuel model D. The model is

$$\hat{P} = 1/(1+\exp(2.83666 - .069199 * ERC)).$$

This logistic model was developed using raw data rather than grouped data. A few values of this function are:

ERC(D)	3	9.5	14	17.5	24	33	40.5	47	56	65	75	90
$\hat{P}$	.067	.102	.134	.164	.236	.365	.491	.602	.739	.840	.913	.967

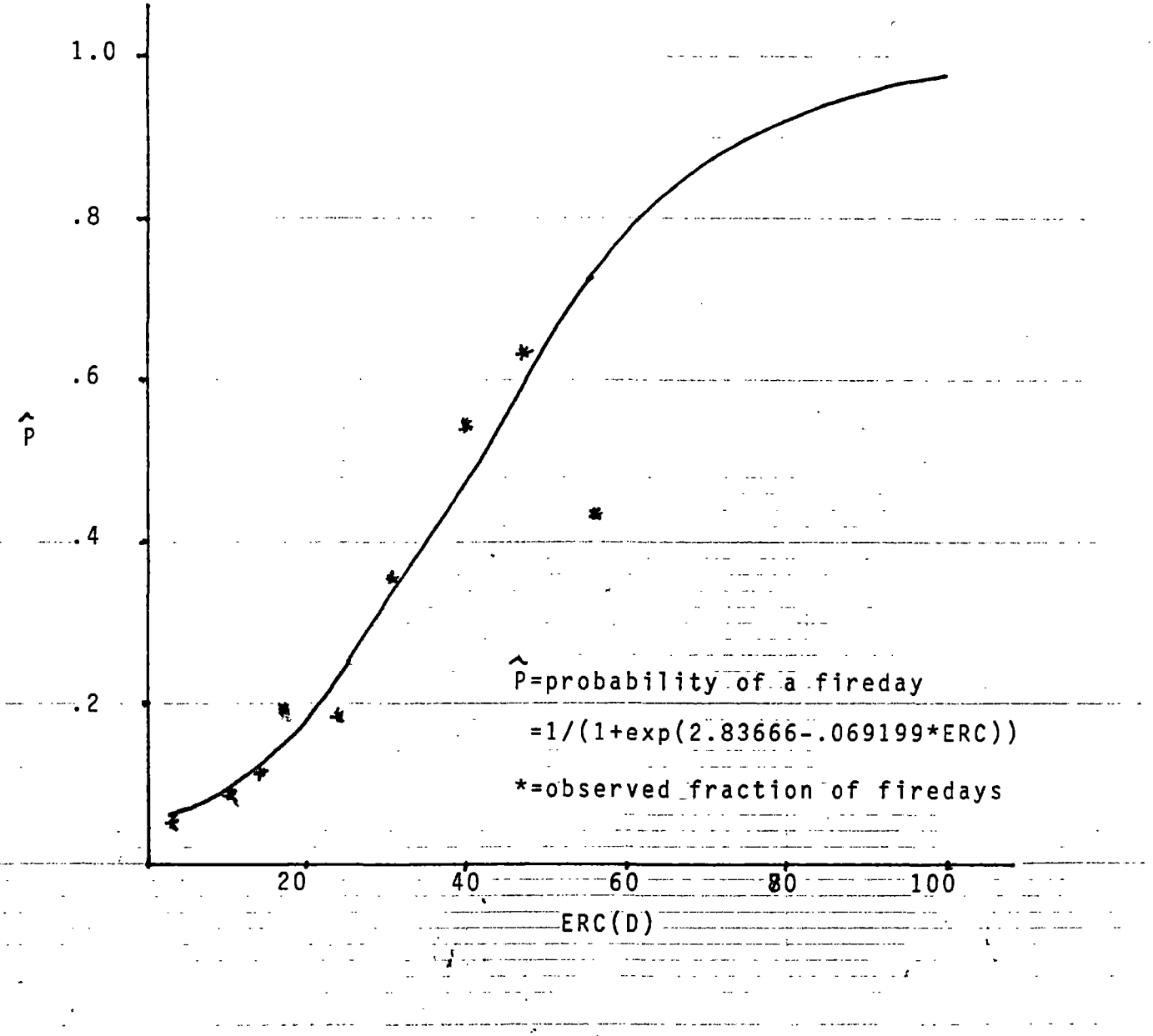
This logistic model is plotted on the following page. The logistic model based on grouped data is very similar:

$$\hat{P} = 1/(1 + \exp(2.79078 - .067077 * ERC)).$$

The table given shortly summarizes, in grouped form, the data that were used to construct these models along with predictions made using these logistic models.

These data can be thought of as 0, 1 data where 1 is a fire day and 0 is a day with no fire. Efron (1978) gave ways of measuring variability in such data sets that are somewhat analogous to ordinary regression sums of squares. These ideas are discussed in more detail in Appendix B. Here we use the measure of variation denoted by S_1 in Efron's paper.

Logistic model for the probability of a fireday



		Observed		Expected (Predicted) Grouped Data Model		Raw Data Model	
ERC(D)	Days	Firedays	Fraction firedays	Firedays	Fraction firedays	Firedays	Fraction firedays
0-6	342	18	.053	23.9	.070	23.0	.067
7-12	412	40	.097	42.8	.104	41.9	.102
13-15	632	87	.138	85.7	.136	84.6	.134
16-19	716	138	.193	118.6	.166	117.7	.164
20-28	513	94	.183	120.5	.235	121.0	.236
29-37	391	142	.363	140.6	.360	142.8	.365
38-43	349	190	.544	168.0	.481	171.5	.491
44-50	288	183	.635	169.8	.589	173.5	.602
51-61	76	33	.434	55.0	.724	56.1	.739
	3719	925					

The overall $\hat{P}$ is 925/3719 = .2487 = fraction firedays. The variation of the data about this overall $\hat{P}$ as measured by Efron's S_1 is called the total sum of squares and is denoted by SS_{TOT}. There is a "best" $\hat{P}$ for each interval which is just the fraction firedays in each interval. These values are found in column 4 of the above table. Each logistic model gives a $\hat{P}$ for each interval using the midpoint of the ERC interval. These are found in columns 6 and 8. For each set of $\hat{P}$'s, one computes a measure of residual variation using Efron's S_1. These are called residual sums of squares and are denoted by SS_{RES}. Finally, for each model we compute explained sum of squares denoted by SS_{EXP} where $SS_{EXP} = SS_{TOT} - SS_{RES}$. For each model we also compute $R^2 = SS_{EXP}/SS_{TOT}$. All of these terms can be interpreted just as they are for ordinary regression. For the example considered here, these sums of squares are summarized in the following table:

Summary for this Example

Model	SS_{TOT}	SS_{RES}	SS_{EXP}	R^2
Best each cell	4172.18	3575.97	596.21	.1429
Logistic (raw)	4172.18	3603.38	568.80	.1363
Logistic (grouped)	4172.18	3625.75	546.43	.1310

For grouped data the "best" $\hat{P}$ in each interval model is the best we can do and gives a standard against which to compare our grouped logistic model. The difference

$$SS_{RES} \text{ (grouped logistic)} - SS_{RES} \text{ ("best" } \hat{P} \text{ each interval)}$$

is a chi-square random variable with 9 - 2 = 7 degrees of freedom that can be used to test whether the "best" $\hat{P}$ model is significantly better than the grouped logistic model. For this example, we have

$X^2 = 3625.75 - 3575.97 = 49.78$ with P-value = .0000.

There is significant lack of fit between the grouped logistic model and the data. This disagreement between data and model can be seen in several of the intervals in the table given earlier. Nevertheless, this model is not too bad. It is among the best one variable models constructed for these data. Much of the problem comes at the highest ERC(D) interval (51-61) where there are many fewer firedays than predicted by the logistic model. This is a problem for much of the Mississippi data considered here. Observed $\hat{P}$'s were also plotted on the earlier graph which gives a graphical picture of how the model fits the data.

The logistic model based on the raw data explains more of SS_{TOT} than does the grouped logistic model, (R^2_{GR} = .1310, R^2_{RA} = .1363 or .0053 X 100% = .53% more). When compared to the "best" $\hat{P}$ model, the raw data logistic model, the results are similar to those for the grouped data model.

A chi-square-like statistic can also be computed to test agreement between a logistic model and the data. This is illustrated for the grouped logistic model. The following table is used:

ERC(D)	Firedays Observed (O)	Firedays Expected (E)	No firedays 0	No firedays E	Total days
0-6	18	23.9	324	318.1	342
7-12	40	42.8	372	369.2	412
13-15	87	85.7	545	546.3	632
16-19	138	118.6	578	597.4	716
20-28	94	120.5	419	392.5	513
29-37	142	140.6	249	250.4	391
38-43	190	168.0	159	181.0	349
44-50	183	169.8	105	118.2	288
51-61	33	55.0	43	21.0	76
					3719

$$X^2=(18-23.9)^2/23.9+...+(33-55)^2/55 + (342-318.1)^2/318.1+...+ (43-21)^2/21$$

$$= 53.14 \quad \text{d.f.} \doteq 9 - 2 = 7 \quad \text{P value} = .0000.$$

This agrees with the test given above using residual sum of squares. The X^2 statistic used here has approximately a limiting chi-square distribution. The degrees of freedom are 9 - 2 since two parameters are estimated for the logistic model.

By way of comparison, a similar analysis is presented below for logistic models based on ERC and fuel model C. Examination of these results clearly shows that these models are not as good as those based on ERC and fuel model D.

		Observed		Expected/Predicted Grouped Data		Raw Data	
ERC(C)	Days	Firedays	Fraction firedays	Firedays	Fraction firedays	Firedays	Fraction firedays
0	534	39	.073	54.5	.102	53.2	.100
1-2	622	95	.153	81.8	.131	80.6	.130
3	516	76	.147	86.6	.168	86.1	.167
4	501	90	.180	98.4	.196	98.3	.196
5-6	598	123	.206	146.9	.246	147.9	.247
7-9	392	179	.457	135.0	.344	137.3	.350
10-14	434	266	.613	230.3	.531	235.8	.543
15-18	103	47	.456	75.0	.728	76.6	.744
19-24	19	10	.526	16.6	.874	16.8	.886
	3719	925					

Measure of variation used is S_1.

$SS_{TOT} = 4172.18$. Overall $\hat{P} = \frac{925}{3719} = .2487$

Models:

Grouped data $\hat{P} = 1/(1 + \exp(2.17515 - .19146 * ERC))$

Raw data $\hat{P} = 1/(1 + \exp(2.20213 - .197986 * ERC))$

Summary Statistics

Model	SS_{TOT}	SS_{RES}	SS_{EXP}	R^2
Best $\hat{P}$ each cell	4172.18	3609.92	562.26	.1348
Logistic (raw)	4172.18	3692.89	479.29	.1149
Logistic (grouped)	4172.18	3705.84	466.34	.1118

Each logistic model is significantly poorer than the best $\hat{P}$ in each cell model as seen by comparing SS_{RES}'s or SS_{EXP}'s or R^2's. These models are constructed from the same fire data as were the preceding models based on ERC and fuel model D. In this case, it makes sense to

compare R^2's. These comparisons indicate that these models are not nearly as good as those based on ERC(D). Examining the table of observed and expected values also clearly shows this.

Models Based on Fire Indexes and Using All Data

Many raw data logistic models were constructed using one or more of the fire indexes and fuel models C and D. The following table summarizes these results giving SS_{RES} and R^2 for each model.

$SS_{TOT} = 4172.18$

Variable(s)	Fuel Model C	D
ERC	3692.89(.1149)*	3603.38(.1363)
BI	3630.03(.1299)	3638.92(.1278)
FLI	3656.85(.1235)	3669.78(.1204)
IC	3717.03(.1091)	3729.92(.1060)
SC	3777.16(.0947)	3792.66(.0910)
ERC,BI	3622.62(.1317)	3589.74(.1396)
BI,FLI	3628.52(.1303)	3636.13(.1285)
ERC, FLI	3629.44(.1301)	3587.53(.1401)
ERC,BI,FLI,IC,SC	3612.38(.1342)	3580.00(.1419)
ERC, ERC^2		3600.86(.1369)

*SS_{RES} (R^2)

The two models based on ERC(C) and ERC(D) were examined in detail earlier. Examining the above table, it is seen that ERC(D) provides the best <u>one</u> variable logistic model in the sense of minimizing SS_{RES} or maximizing R^2. Results for some two variable models as well as a model containing all five fire indexes are also given.

As an example, testing the following hypotheses is illustrated:

H_0: No difference in model with ERC(D) above and model containing all five variables.

H_1: There is a difference.

The difference in SS_{RES}'s has an approximate chi-square distribution with 4 d.f.

$X^2 = 3603.38 - 3580.00 = 23.38$ P-value = .0001.

The model with five variables is significantly better.

Note that there are a couple of two variable models that appear to be nearly as good as the 5 variable model.

Also note that, in nearly every case, the models based on fuel model D are better than the corresponding ones based on fuel model C.

Three of the particular logistic models summarized in the above table are given below.

BI(C) (FUEL MODEL C) $SS_{RES} = 3630.03$ $R^2 = .1299$

$\hat{P} = 1/(1 + \exp(2.06888 - .088553 * BI))$

ERC(D) and BI(D) $SS_{RES} = 3589.74$ $R^2 = .1396$

$\hat{P} = 1/(1 + \exp(2.76434 - .046977 * ERC - .013292 * BI))$

ERC(D) and FLI(D) $SS_{RES} = 3587.53$ $R^2 = .1401$

$\hat{P} = 1/(1 + \exp(2.81055 - .049001 * ERC - .018013 * FLI))$

Models Based on Months January - April, October - December

Many raw data logistic models were constructed using only 7 months each year--the 7 months when most fires occur. These results are summarized in the table that follows. These models are based on a different data set than those for the entire year so that R^2's are not directly comparable with those for the models presented earlier based on all data. The best single variable model is based on ERC(D) again and a more detailed analysis of this model is given following the table.

$SS_{TOT} = 2901.72$

	Fuel Model	
Variable(s)	C	D
ERC	2630.56(.0934)*	2603.20(.1029)
BI	2609.76(.1006)	2638.66(.0907)
FLI	2637.84(.0909)	2671.37(.0794)
IC	2659.63(.0834)	2656.15(.0846)
SC	2716.08(.0640)	2740.34(.0556)
ERC, BI, FLI, IC, SC	2594.97(.1057)	2591.91(.1068)

*SS_{RES} (R^2)

In addition to the model analyzed in detail in the next table, two other models are given here. Both are constructed from the raw data.

Fuel Model C - BI(C) $SS_{RES} = 2609.76$ $R^2 = .1006$

$\hat{P} = 1/(1 + \exp(1.68241 - .072129 * BI))$

Fuel Model D - BI(D) $SS_{RES} = 2638.66$ $R^2 = .0907$

$\hat{P} = 1/(1 + \exp(1.95862 - .028972 * BI))$

Detailed analysis of a model based on data in months October-April only.

		Observed		Expected/Predicted Grouped data model	
ERC(D)	Days	Firedays	Fraction firedays	Firedays	Fraction firedays
0-6	208	17	.082	23.6	.114
7-12	232	31	.134	35.6	.154
13-15	238	57	.240	44.6	.188
16-19	217	65	.300	47.2	.218
20-28	279	52	.186	78.8	.283
29-37	382	138	.361	148.6	.389
38-43	349	190	.544	170.1	.487
44-50	288	183	.635	165.2	.574
51-61	76	33	.434	52.1	.685
	2269	766			

Measure of variation used is S_1 .

SS_{TOT} = 2901.22. Overall $\hat{P}$ = 766/2269 = .338

Model:

Grouped data $\hat{P} = 1/(1 + \exp(2.21373 - .053412 * ERC))$

Summary Statistics

Model	SS_{TOT}	SS_{RES}	SS_{EXP}	R^2
Best $\hat{P}$ each interval	2901.22	2558.23	342.99	.1182
Logistic (grouped)	2901.22	2617.63	283.59	.0977

To test H_0: "best" P model is no better than the logistic model.

We use the difference in SS_{RES}'s with d.f. = 7.

X^2 = 2617.63 - 2558.23 = 59.40 P-value = .000.

There is significant lack of fit.

Models Based on Data During the Fire Season, 10/1-12/15, 2/15-4/30

Many raw data logistic models were constructed using only data from the fire season. These results are summarized in the table below. These models are based on a different data set than were earlier models so again R^2's are not directly comparable with R^2's for the earlier models. The best single variable model is again based on ERC(D) and a more detailed analysis of this model is given following the table.

$SS_{TOT} = 2047.63$

Variable(s)	Fuel Model C	D
ERC	1897(.0733)*	1877.20(.0832)
BI	1883(.0804)	1889.82(.0771)
FLI	1888.44(.0774)	1898.47(.0728)
IC	1919.4(.0626)	1917.57(.0635)
SC	1933.3(.0558)	1941.94(.0516)
ERC, BI, FLI, IC, SC	1870.95(.0863)	1868.03(.0877)

*SS_{RES} (R^2)

A detailed analysis of a model based on data during fire season 10/1-12/15, 2/15-4/30.

		Observed		Expected/Predicted Grouped data model	
ERC(D)	Days	Firedays	Fraction firedays	Firedays	Fraction firedays
0-6	132	13	.099	17.9	.136
7-12	204	30	.147	35.7	.175
13-15	221	54	.244	45.9	.208
16-19	201	62	.309	47.4	.236
20-28	198	40	.202	58.3	.295
29-37	211	81	.384	81.9	.388
38-43	212	111	.524	100.5	.474
44-50	181	107	.591	99.4	.549
51-61	63	30	.476	40.9	.650
	1623	528			

Measure of variation used is S_1.

SS_{TOT} = 2047.63. Overall $\hat{P}$ = 528/1623 = .325.

Model:

Grouped data $\hat{P} = 1/(1 + \exp(1.99159 - .046589 * ERC))$

Summary Statistics

Model	SS_{TOT}	SS_{RES}	SS_{EXP}	R^2
Best $\hat{P}$ each interval	2047.63	1855.23	192.40	.0940
Logistic (grouped)	2047.63	1885.47	162.16	.0792

Formal tests show there is significant lack of fit between this model and the data.

Models Based on Only Fires with Cause Incendiary

The cause of fires for the data set considered here was incendiary about 76 percent of the time. Many raw data models were constructed using only these fires and data for all months, as well as using data for only the months January-April or October-December. These results are summarized in tables that follow. Following these tables, a more detailed analysis is presented for one model based on BI(D) and data from all months. Generally speaking, these models are similar to models constructed using all fires.

Logistic models for fires with cause incendiary.

Data used: All months, only fires with cause incendiary.

SS_{TOT} = 3666.43 Days = 3719 Firedays = 724

Variable(s)	Fuel Model C	D
ERC	3227.45(.1197)*	3091.53(.1568)
BI	3087.84(.1578)	3069.42(.1628)
FLI	3108.03(.1523)	3087.96(.1578)
IC	3220.55(.1216)	3260.65(.1107)
SC	3201.09(.1269)	3211.45(.1241)
ERC BI	3087.40(.1579)	3047.05(.1689)
ERC FLI	3103.12(.1536)	3041.16(.1705)
ERC IC	3200.38(.1271)	3091.53(.1568)
BI FLI	3084.64(.1587)	3062.05(.1648)
BI IC	3080.30(.1599)	3068.25(.1632)
ERC BI IC	3079.75(.1600)	3045.08(.1695)
ERC BI FLI	3084.30(.1588)	3039.45(.1710)
ERC BI FLI IC SC	3069.79(.1627)	3030.48(.1735)

*$SS_{RES}(R^2)$

A detailed analysis of a model based on data in all months but only fires with cause incendiary.

		Observed		Expected/Predicted Grouped data model	
BI(D)	Days	Firedays	Fraction firedays	Firedays	Fraction firedays
0	179	12	.067	8.7	.049
1-10	244	7	.029	14.7	.060
11-14	572	35	.061	44.8	.078
15-18	726	64	.088	65.9	.091
19-24	434	44	.101	47.2	.109
25-40	366	57	.156	58.6	.160
41-58	486	161	.331	133.5	.275
59-69	350	163	.466	141.7	.405
70-80	220	103	.468	113.3	.515
81-92	104	53	.510	65.3	.628
93-122	38	25	.658	30.3	.798
	3719	724			

Measure of variation used is S_1.

SS_{TOT} = 3666.43. Overall $\hat{P}$ = 724/3719 = .195

Model:

Grouped data $\hat{P} = 1/(1 + \exp[2.97113 - .040407 * BI])$

Summary Statistics

Model	SS_{TOT}	SS_{RES}	SS_{EXP}	R^2
Best $\hat{P}$ each interval	3666.43	3047.30	619.13	.1689
Logistic (grouped)	3666.43	3081.38	585.05	.1596

Considering the type of fires we are using here, this model seems to be very good. Formal tests, however, do show lack of fit.

Logistic models for fires with cause incendiary.

Data used: Months October through April, only fires with cause incendiary.

SS_{TOT} = 2739.68 Days = 2269 Firedays = 662

Variable(s)	Fuel Model C	D
ERC	2519.36(.0804)*	2479.62(.0949)
BI	2474.63(.0967)	2485.45(.0928)
FLI	2498.08(.0882)	2511.91(.0831)
IC	2539.26(.0732)	2539.86(.0729)
SC	2549.59(.0694)	2567.31(.0629)
ERC, BI	2473.81(.0970)	2465.15(.1002)
ERC, FLI	2485.98(.0926)	2467.03(.0995)
ERC,IC	2515.49(.0818)	2477.78(.0956)
BI, FLI	2474.57(.0968)	2484.79(.0930)
BI, IC	2471.73(.0978)	2479.06(.0951)
ERC, BI, IC	2468.10(.0991)	2464.97(.0992)
ERC, BI, FLI	2473.74(.0971)	2464.47(.1005)
ERC,BI,FLI,IC,SC	2466.64(.0997)	2463.22(.1009)

* SS_{RES} (R^2)

Models Based on All Data and Weather Variables

Models were constructed using all data and weather variables in many combinations. These results are summarized in the table below. Following this table a more detailed analysis is given for one of these models. The best single variable models are those based on MOISHERB or MOISWOOD. The best two variable models are MOISWOOD and FUELMOI1 (1-hour fuel moisture) and MOISHERB and FUELMOI1. The last two models, in fact, are a little better than any of the models constructed using fire indexes as measured by R^2.

Data used: all months

SS_{TOT} = 4172.18

Variable(s)	SS_{RES} (R^2)	Variable(s)	SS_{RES} (R^2)
HUMRISK	4169.19(.0007)	MOISHERB FUELMOI1	3582.02(.1415)
TEMP	4072.56(.0239)	MOISHERB PRECTIME	3635.55(.1286)
MAXTEMP	4040.21(.0316)	PRECAMT MOISHERB	3668.18(.1208)
PRECTIME	4023.26(.0357)	MOISWOOD RELHUMID	3641.56(.1272)
PRECAMT	4032.04(.0336)	MOISWOOD FUELMOI1	3571.32(.1440)
FUELMOI1	3967.18(.0491)	MOISWOOD PRECTIME	3630.05(.1299)
FUELMOI2	4101.25(.0170)	MOISWOOD PRECAMT	3666.77(.1211)
FUELMOI3	4097.38(.0179)	RELHUMID FUELMOI1	3917.13(.0611)
FUELMOI4	4168.41(.0009)	RELHUMID PRECTIME	3862.03(.0743)
MOISWOOD	3813.60(.0859)	RELHUMID PRECAMT	3860.69(.0747)
MOISHERB	3808.66(.0871)	FUELMOI1 PRECTIME	3934.74(.0569)
RELHUMID	3920.82(.0602)	FUELMOI1 PRECAMT	3927.88(.0586)
MOISWOOD MOISHERB	3806.91(.0875)	PRECTIME PRECAMT	4006.30(.0398)
MOISHERB RELHUMID	3646.05(.1261)		
		MOISHERB MOISWOOD FUELMOI1 RELHUMID PRECAMT PRECTIME	3524.25(.1553)

A few specific logistic models based on weather variables and using all data are:

MOISHERB $SS_{RES} = 3808.66$ $R^2 = .0871$

$\hat{P} = 1/(1 + \exp(.236063 + .0106504 * \text{MOISHERB}))$

RELHUMID $SS_{RES} = 3920.82$ $R^2 = .0602$

$\hat{P} = 1/(1 + \exp(-.687347 + .033462 * \text{RELHUMID}))$

MOISHERB, FUELMOIS1 $SS_{RES} = 3582.02$ $R^2 = .1415$

$\hat{P} = 1/(1 + \exp(-1.2343 + .0112079 * \text{MOISHERB} + .14817 * \text{FUELMOI1}))$

MOISWOOD, FUELMOI1 $SS_{RES} = 3571.32$ $R^2 = .1440$

$\hat{P} = 1/(1 + \exp(-2.4693 + .018540 * \text{MOISWOOD} + .151822 * \text{FUELMOI1}))$

A detailed analysis of a model based on MOISWOOD and using all data:

		Observed		Expected/Predicted Grouped data model	
MOISWOOD	Days	Firedays	Fraction firedays	Firedays	Fraction firedays
70	1418	580	.409	581.7	.410
71-100	36	6	.167	12.6	.349
101-120	30	12	.400	7.8	.260
121-140	484	103	.213	97.1	.201
141-150	580	110	.190	94.6	.163
151-160	353	42	.119	49.9	.141
161-175	351	30	.086	41.3	.118
176-190	233	26	.112	21.9	.094
191-200	234	16	.068	18.1	.077
	3719	925		925	

Measure of variation used is S_1.

$SS_{TOT} = 4172.18$. Overall $\hat{P} = 925/3719 = .2487$.

Model:

Grouped data $\hat{P} = 1/(1 + \exp(-.816323 + .0168485 * \text{MOISWOOD}))$

Summary Statistics

Model	SS_{TOT}	SS_{RES}	SS_{EXP}	R^2
Best $\hat{P}$ each interval	4172.18	3798.20	373.98	.0896
Logistic (grouped)	4172.18	3816.70	355.48	.0852

Chapter 3. Mississippi

Districts: Bude (04), Homochitto (08)

Weather Station: Bude (226102)

THE DATA

Data used were from the two districts that use the Bude Weather Station (226102) in Mississippi. The districts used were Bude (04) and Homochitto (08). Years studied were 1973-1987 with fairly complete weather data through the first 6 months of 1987.

WEATHER DATA FILE

Weather data were retrieved from the National Fire Weather Data Library. Variables retrieved are listed in Appendix A. The Bude weather station operates year-round. After the weather data were retrieved, NFDRS indexes were computed for each day using FIRDAT for several fuel models (C, D, and G for this study). Occasionally, several days in a row had missing weather data. These missing weather data were estimated and filled in using linear interpolation. In this study, days that were in a string of 8 or more missing weather days were not used. Some summary statistics follow:

Missing days	0	1	2	3	4	5	
Frequency (days)	5152	56	20	15	8	10	5261
Number of instances	5152	56	10	5	2	2	

Year	73	74	75	76	77	78	79	80	81	82
Days of useable weather	364	334	355	366	365	365	365	366	365	365

83	84	85	86	87	
365	366	365	365	190	5261

Month	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep
Days of useable weather	464	423	434	420	434	420	458	455	450

Oct	Nov	Dec	
449	420	434	5261

Summary Statistics on Weather Variables and Fire Indexes

N=5261

Variable	Mean	Minimum	Maximum	Standard deviation
Temperature	73.6	20	101	14.7
Relative humidity	59.4	5	100	19.9
Windspeed	2.1	0	8	1.0
Maximum temperature	76.3	21	102	14.5
Minimum temperature	55.4	3	87	14.5
Maximum humidity	95.9	28	100	10.0
Minimum humidity	54.2	1	100	18.4
Precipitation time (hours)	1.0	0	24	2.8
Precipitation amount	17.4	0	755	52.6
1-hour fuel moisture	11.8	2	32	6.5
10-hour fuel moisture	16.1	2	69	11.1
100-hour fuel moisture	18.5	9	43	3.1
1000-hour fuel moisture	20.9	13	49	3.7
Woody moisture	119.5	70	200	42.7
Herbaceous moisture	90.2	2	250	68.0
Fuel Model C				
IC	7.0	0	60	8.1
SC	3.3	0	29	4.4
ERC	4.7	0	23	4.0
BI	9.4	0	50	9.4
FLI	7.1	0	35	6.7
Fuel Model D				
IC	8.6	0	58	8.3
SC	9.3	0	57	9.3
ERC	21.2	0	60	13.7
BI	32.0	0	113	24.1
FLI	24.1	0	80	16.8
Fuel Model G				
IC	9.3	0	55	7.5
SC	4.1	0	21	2.8
ERC	19.2	0	48	9.8
BI	20.8	0	56	10.4
FLI	15.4	0	40	6.9

FIRE DATA

Data for fires for the Mississippi districts of Bude and Homochitto were retrieved from the National Fire Occurrence Data Library. This file had one case for each fire in each district for years 1973-1987. A case was added to this file for each day in each district that did not have a fire. A list of variables taken from the NFODL is given in Appendix A. Summary information on the fires on days with useable weather data is given in the following tables.

District	Number of Fires
Bude	109
Homochitto	95
	204

Size	Number of fires
0 - .25 acres	21
.26 - 9 acres	115
10 - 99 acres	64
100 - 299 acres	3
300 - 999 acres	1
	204

Year	73	74	75	76	77	78	79	80	81	82
Number of fires	5	0	5	11	12	25	17	14	32	11

83	84	85	86	87*	
6	8	12	37	9	204

*only 6 months

Discovery month	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	
Number of fires	19	32	65	10	8	9	6	4	3	20	16	12	204

Cause	Number of fires
Lightning	3
Equipment use	8
Smoking	9
Campfire	4
Debris burning	33
Incendiary	113
Children	2
Miscellaneous	32
	204

MERGED DATA FILE

The weather and the fire data files were merged. Weather data and fire indexes were attached to each case in the fire data file. Cases in the fire data file with no weather/fire index data were deleted. At this point many days have several cases (one for each fire that day). The cases for each day are collapsed to one case with number of fires and number of large fires on a day computed and added to the case for each day. This final merged data file was constructed using fires from both districts.

Number of Days with K Fires

Number of fires (K)	0	1	2	3	4	
Number of days with K fires	5102	127	22	7	3	5261

Number of Days with K Large Fires*

Number of large fires (K)	0	1	2	3	
Number of days with K large fires	5210	37	11	3	5261

* Large fire - 10 acres or larger

Although not reported here, tables such as the following were constructed for all fire indexes and all fuel models.

Number of Days with K Fires by BI(C)

BI(C) \ No. of fires	0	1	2	3	4	
0	844	6	1	0	0	851
1-3	695	6	2	0	0	703
4	669	11	4	0	0	684
5	648	10	1	0	0	659
6-8	522	6	0	0	0	528
9-16	489	16	3	1	0	509
17-21	504	17	1	2	0	524
22-26	411	24	4	2	2	443
27-36	299	26	6	2	1	334
37-50	21	5	0	0	0	26
	5102	127	22	7	3	5261

The next several tables give summary information about the NFDRS fire indexes ERC, BI, IC, FLI, SC for fuel models C, D, and G, firedays and large firedays for all fires.

Summary statistics relating fire indexes, fire days[1] and large fire days[2]

ERC(C)[3]	Days	Firedays		Large firedays	
0	885	7	.008	3	.003
1	260	2	.008	1	.004
2	559	6	.011	2	.004
3	746	21	.028	7	.009
4	688	13	.019	3	.004
5	473	4	.009	1	.002
6-8	714	25	.035	4	.006
9-11	528	42	.080	12	.023
12-16	373	36	.097	17	.046
17-23	35	3	.086	1	.029
	5261	159		51	

ERC2(D)[4]	Days	Firedays		Large firedays	
0	400	4	.010	2	.005
1-8	408	1	.003	0	.000
9-12	521	5	.010	1	.002
13-15	842	18	.021	6	.007
16-18	710	15	.021	5	.007
19-23	533	3	.006	0	.000
24-32	521	17	.033	2	.004
33-39	547	31	.057	9	.017
40-44	426	28	.064	9	.021
45-51	330	34	.103	17	.051
52-60	23	3	.130	0	.000
	5261	159		51	

ERC3(G)[5]	Days	Firedays		Large firedays	
0-2	513	4	.008	1	.002
3-8	359	2	.006	2	.006
9-14	569	7	.012	2	.004
15-18	660	17	.026	5	.008
19-21	735	15	.020	3	.004
22-23	533	16	.030	4	.008
24-25	578	25	.043	11	.019
26-28	544	24	.044	12	.022
29-32	435	23	.053	7	.016
33-41	294	25	.085	4	.014
42-48	41	1	.024	0	.000
	5261	159		51	

[1] Day with at least one fire
[2] Day with at least one fire 10 acres or larger
[3] Fuel model C
[4] Fuel model D
[5] Fuel model G

BI1(C)	Days	Firedays		Large firedays	
0	851	7	.008	3	.004
1-3	703	8	.011	6	.009
4	684	15	.022	2	.003
5	659	11	.017	2	.003
6-8	528	6	.011	2	.004
9-16	509	20	.039	2	.004
17-21	524	20	.038	5	.010
22-26	443	32	.072	14	.032
27-36	334	35	.105	13	.039
37-50	26	5	.192	2	.077
	5261	159		51	

BI2(D)	Days	Firedays		Large firedays	
0	426	6	.014	3	.007
1-11	362	0	.000	0	.000
12-15	717	10	.014	5	.007
16-18	659	11	.017	1	.002
19-23	618	12	.019	4	.007
24-37	646	8	.012	1	.002
38-52	520	24	.046	3	.006
53-64	575	30	.052	13	.023
65-72	366	21	.057	7	.019
73-89	322	31	.096	12	.037
90-113	50	6	.120	2	.040
	5261	159		51	

BI3(G)	Days	Firedays		Large firedays	
0	520	6	.012	3	.006
1-11	340	0	.000	0	.000
12-16	548	5	.009	2	.004
17-19	584	11	.019	6	.010
20-21	477	4	.008	2	.004
22-24	840	21	.025	5	.006
25-27	651	26	.040	3	.005
28-30	503	20	.040	7	.014
31-34	429	27	.063	9	.021
35-45	338	35	.104	12	.036
46-56	31	4	.129	2	.065
	5261	159		51	

IC1(C)	Days	Firedays		Large firedays	
0	1106	11	.001	5	.005
1	335	4	.012	0	.000
2	551	9	.016	3	.005
3	504	8	.016	3	.006
4	401	9	.022	1	.003
5-6	530	8	.015	3	.006
7-10	571	16	.028	4	.007
11-15	447	24	.054	6	.013
16-22	472	35	.074	11	.023
23-32	279	24	.086	10	.036
33-60	65	11	.169	5	.077
	5261	159		51	

IC2(D)	Days	Firedays		Large firedays	
0	969	9	.009	4	.004
1-3	750	11	.015	2	.003
4-5	761	13	.017	4	.005
6-8	721	14	.019	4	.006
9-11	555	17	.031	5	.009
12-15	484	19	.039	5	.010
16-20	474	27	.057	8	.017
21-25	294	23	.078	10	.034
26-34	197	16	.081	5	.025
35-58	56	10	.179	4	.071
	5261	159		51	

IC3(G)	Days	Firedays		Large firedays	
0	966	9	.009	4	.004
1-4	555	9	.016	1	.002
5-6	579	13	.023	5	.009
7-8	637	12	.019	2	.003
9-11	761	18	.024	7	.009
12-14	582	25	.043	6	.010
15-17	460	18	.039	7	.015
18-21	375	21	.056	6	.016
22-32	304	25	.082	10	.033
33-55	42	9	.214	3	.071
	5261	159		51	

FLI1(C)	Days	Firedays		Large firedays	
0	645	2	.003	1	.002
1-2	726	8	.010	6	.008
3	705	15	.021	2	.003
4	996	17	.017	4	.004
5-10	634	16	.025	2	.003
11-14	567	23	.041	4	.007
15-18	604	36	.060	16	.027
19-26	364	37	.112	14	.039
27-35	20	5	.250	2	.100
	5261	159		51	

FLI2(D)	Days	Firedays		Large firedays	
0-6	395	1	.003	1	.003
7-10	682	7	.010	4	.006
11-12	701	9	.013	2	.003
13-15	673	12	.018	2	.003
16-22	585	9	.015	2	.003
23-34	627	20	.032	3	.005
35-42	541	21	.039	6	.011
43-49	523	33	.063	13	.025
50-54	282	16	.057	5	.018
55-65	214	26	.122	11	.051
66-80	38	5	.132	2	.053
	5261	159		51	

FLI3(G)	Days	Firedays		Large firedays	
0-2	398	1	.003	1	.003
3-9	2070	33	.016	6	.003
10-12	512	6	.012	5	.010
13-14	296	4	.014	3	.010
15-16	306	7	.023	2	.007
17-18	340	16	.047	5	.015
19-21	518	24	.046	5	.010
22-24	431	27	.063	9	.021
25-33	373	38	.102	13	.035
34-40	17	3	.177	1	.118
	5261	159		51	

SC1(c)	Days	Firedays		Large firedays	
0	1381	19	.014	9	.007
1	1815	26	.014	5	.003
2-4	556	21	.038	2	.004
5-7	587	30	.051	14	.024
8-11	579	30	.052	8	.014
12-16	275	26	.095	11	.040
17-29	68	7	.103	2	.039
	5261	159		51	

SC2(D)	Days	Firedays		Large firedays	
0	360	6	.017	3	.008
1	159	2	.013	1	.006
2	719	10	.014	4	.006
3	833	7	.008	1	.001
4	456	6	.013	2	.004
5-7	610	14	.023	2	.003
8-12	572	18	.032	1	.002
13-17	549	33	.060	15	.027
18-23	480	25	.052	7	.015
24-28	278	13	.047	5	.018
29-36	186	20	.108	9	.048
37-57	59	5	.085	1	.017
	5261	159		51	

SC3(G)	Days	Firedays		Large firedays	
0-1	679	6	.009	3	.004
2	733	13	.018	6	.008
3	1138	16	.014	3	.003
4	841	24	.029	3	.004
5	582	22	.038	9	.016
6-7	675	30	.044	8	.012
8-9	351	21	.060	8	.023
10-15	245	25	.102	10	.041
16-21	17	2	.118	1	.059
	5261	159		51	

Summary Statistics Relating Weather Variables, Fire Days and Large Fire Days

RELHUMID	Days	Firedays		Large firedays	
5-30	246	28	.114	7	.029
31-38	527	25	.047	12	.023
39-47	803	28	.035	8	.010
48-54	766	25	.033	9	.012
55-62	856	25	.029	6	.007
63-70	704	7	.010	2	.003
71-81	577	12	.021	3	.005
82-92	279	3	.011	2	.007
93-99	122	1	.008	0	.000
100	381	5	.013	2	.005
	5261	159		51	

HUMRISK	Days	Firedays		Large firedays	
0	5161	153	.030	48	.009
1	100	6	.060	3	.030
	5261	159		51	

PRECTIME	Days	Firedays		Large firedays	
0	4008	146	.036	45	.011
1	430	4	.009	3	.007
2-3	312	2	.006	1	.003
4-6	267	2	.008	1	.004
7-10	130	2	.015	1	.008
11-15	64	2	.031	0	.000
16-24	50	1	.020	0	.008
	5261	159		51	

PRECAMT	Days	Firedays		Large firedays	
0	4008	146	.036	45	.011
1-10	207	3	.015	3	.015
11-28	258	1	.004	0	.000
29-58	261	2	.008	1	.004
59-84	157	2	.013	2	.013
85-130	163	4	.025	0	.000
131-188	104	1	.010	0	.000
189-260	52	0	.000	0	.000
261-400	38	0	.000	0	.000
401-755	13	0	.008	0	.008
	5261	159		51	

FUELMOI1*	Days	Firedays		Large firedays	
2-5	216	24	.111	8	.037
6	425	26	.061	9	.021
7	623	17	.027	6	.010
8	570	21	.037	7	.012
9	605	16	.026	5	.008
10	634	22	.035	8	.013
11	469	9	.019	2	.004
12-13	527	11	.021	2	.004
14-17	432	5	.012	0	.000
18-22	239	3	.013	2	.008
23-28	231	1	.004	0	.000
29-32	290	4	.014	2	.007
	5261	159		51	

FUELMOI2	Days	Firedays		Large firedays	
2-6	375	7	.019	1	.003
7	240	6	.025	2	.008
8	308	17	.055	7	.023
9	390	19	.049	5	.013
10	480	14	.029	4	.008
11	419	28	.067	14	.033
12-13	829	34	.041	7	.008
14-15	643	18	.028	4	.006
16-20	599	9	.015	3	.005
21-28	362	2	.006	1	.003
29-40	284	1	.004	1	.004
41-50	326	4	.012	2	.006
51-69	6	0	.000	0	.000
	5261	159		51	

FUELMOI3	Days	Firedays		Large firedays	
9-13	194	13	.067	3	.016
14	186	19	.102	6	.032
15	266	13	.049	4	.015
16	491	23	.047	8	.016
17	837	33	.039	13	.016
18	981	25	.026	5	.005
19	744	19	.026	7	.009
20	490	6	.012	1	.002
21-22	580	6	.010	4	.007
23-24	249	2	.008	0	.000
25-28	195	0	.000	0	.000
29-43	48	0	.000	0	.000
	5261	159		51	

FUELMOI4	Days	Firedays		Large firedays	
13-16	293	15	.051	0	.000
17	288	8	.028	2	.007
18	640	39	.061	12	.019
19	865	23	.027	9	.010
20	797	22	.028	9	.011
21	568	16	.028	6	.011
22	501	15	.030	7	.014
23-24	645	12	.019	3	.005
25-26	269	4	.015	1	.004
27-31	301	5	.017	2	.007
32-34	45	0	.000	0	.000
35-49	49	0	.000	0	.000
	5261	159		51	

*FUELMOI1, FUELMOI2, FUELMOI3, FUELMOI4 are the 1-hr, 10-hr, 100-hr, and 1000-hr fuel moistures, respectively.

TEMP	Days	Firedays		Large firedays	
20-40	169	4	.024	1	.006
41-57	649	14	.022	8	.012
58-64	514	18	.035	6	.012
65-72	825	34	.041	15	.018
73-76	491	23	.047	7	.014
77-80	591	27	.046	11	.019
81-85	674	24	.036	1	.002
86-90	898	8	.009	1	.001
91-92	252	4	.016	1	.004
93-94	116	1	.009	0	.000
95-101	82	2	.024	0	.000
	5261	159		51	

MAXTEMP	Days	Firedays		Large firedays	
21-42	155	3	.019	0	.000
43-54	359	9	.025	6	.017
55-63	493	14	.028	7	.014
64-70	634	25	.039	10	.016
71-77	737	37	.050	14	.019
78-82	776	35	.045	11	.014
83-88	873	19	.022	1	.001
89-91	485	7	.014	1	.002
92-93	391	6	.015	1	.003
94-95	193	2	.010	0	.000
96-102	165	2	.012	0	.000
	5261	159		51	

MOISHERB	Days	Firedays		Large firedays	
2-6	340	37	.109	17	.050
7-8	442	24	.054	8	.018
9-12	579	30	.052	11	.019
13-27	479	10	.021	3	.006
28-100	490	17	.035	2	.004
101-120	842	14	.017	2	.002
121-140	754	15	.020	3	.004
141-158	560	8	.014	5	.009
159-173	287	1	.004	0	.000
174-194	227	1	.004	0	.000
195-226	158	1	.006	0	.000
227-250	103	1	.010	0	.000
	5261	159		51	

MOISWOOD	Days	Firedays		Large firedays	
70	2031	105	.052	41	.020
71-100	41	0	.000	0	.000
101-133	540	20	.037	0	.000
134-145	769	17	.022	5	.007
146-157	842	11	.013	3	.004
158-171	516	3	.006	1	.002
172-184	273	2	.007	1	.004
185-192	88	0	.000	0	.000
193-200	161	1	.006	0	.000
	5261	159		51	

Models Based on Fire Indexes and Using All Data

Many raw data logistic models for FIREDAY were constructed using one or more of the fire indexes and fuel models C, D, and G. The following table summarizes these results giving SS_{RES} and R^2 for each model.

$SS_{TOT} = 1425.88$

	Fuel Model		
Variables	C	D	G
ERC	1321.00(.074)*	1317.40(.076)	1370.55(.039)
BI	1314.94(.078)	1328.26(.068)	1321.15(.073)
IC	1327.43(.069)	1332.05(.066)	1347.19(.055)
FLI	1310.61(.081)	1321.11(.073)	1309.04(.082)
SC	1351.03(.052)	1356.56(.049)	1361.17(.045)
ERC BI	1310.95(.081)	1316.12(.077)	1320.78(.074)
FLI BI	1308.89(.082)	1319.58(.075)	1307.32(.083)
FLI IC	1308.61(.082)	1311.86(.080)	1304.55(.085)
FLI ERC	1304.78(.085)	1309.56(.082)	1306.91(.083)
ERC BI IC	1310.93(.081)	1314.11(.078)	1316.71(.077)
(ERC BI IC SC FLI)	1300.87(.088)	1304.58(.085)	1303.40(.086)

*SS_{RES} (R^2)

Several specific models summarized in the table above are given below. Data from all months was used in constructing these models and $SS_{TOT} = 1425.88$.

FLI Fuel model C: $SS_{RES} = 1310.61$ $R^2 = .081$

$$\hat{P} = 1/(1 + \exp(4.57745 - .1123 * FLI))$$

Fuel model D: $SS_{RES} = 1321.11$ $R^2 = .073$

$$\hat{P} = 1/(1 + \exp(4.88672 - .046097 * FLI))$$

Fuel model G: $SS_{RES} = 1309.04$ $R^2 = .082$

$$\hat{P} = 1/(1 + \exp(5.9375 - .135745 * FLI))$$

BI Fuel model C: $SS_{RES} = 1314.94$ $R^2 = .078$

$$\hat{P} = 1/(1 + \exp(4.4893 - .077442 * BI))$$

FLI, ERC Fuel model C: $SS_{RES} = 1304.78$ $R^2 = .085$

$$\hat{P} = 1/(1 + \exp(4.67777 - .07856 * FLI - .069374 * ERC))$$

FLI, IC Fuel model G: $SS_{RES} = 1304.55$ $R^2 = .085$

$$\hat{P} = 1/(1 + \exp(5.81763 - .113016 * FLI - .024988 * IC))$$

A detailed analysis of logistic models for FIREDAY using FLI(C) and all data.

		Observed		Expected (Predicted) Grouped Data		Raw Data	
FLI(C)	Days	Firedays	Fraction firedays	Firedays	Fraction firedays	Firedays	Fraction firedays
0	645	2	.003	6.8	.011	6.6	.010
1-2	726	8	.011	9.0	.012	8.7	.012
3	705	15	.021	10.3	.015	10.0	.014
4	996	17	.017	16.1	.016	15.8	.016
5-10	634	16	.025	14.8	.023	14.8	.023
11-14	567	23	.041	22.4	.039	22.8	.040
15-18	604	36	.060	35.9	.059	37.2	.062
19-26	364	37	.102	39.1	.107	41.5	.114
27-35	20	5	.250	4.6	.231	5.0	.251
	5261	159					

Measurement of variation is S_1. $SS_{TOT} = 1425.88$ Overall $\hat{P} = 159/5261 = .0302$

Models:

Grouped data: $\hat{P} = 1/(1 + \exp(4.53744 - .107551 * FLI)$

Raw data: $\hat{P} = 1/(1 + \exp(4.57745 - .1123 * FLI))$

Summary Statistics

Model	SS_{TOT}	SS_{RES}	SS_{EXP}	R^2
Best $\hat{P}$ each interval	1425.88	1308.86	117.02	.082
Logistic (raw)	1425.88	1310.61	115.27	.081
Logistic (grouped)	1425.88	1316.05	109.83	.077

Both models fit the data very well. The test statistic for comparing the logistic model (grouped) and the "best" $\hat{P}$ model is

$X^2 = 1316.05 - 1308.86 = 7.19$ d.f. = 7 P value = .4094.

Models based on fire indexes for large firedays using all data.

Many raw data logistic models for LFIREDAY were constructed. The following table summarizes these results giving SS_{RES} and R^2 for each model. A few of the specific models are given and a detailed analysis of one model is shown.

$SS_{TOT} = 574.40$

	Fuel model		
Variables	C	D	G
ERC	531.19(.075)	526.18(.084)	564.19(.018)
BI	527.60(.081)	533.36(.071)	544.67(.052)
IC	535.02(.069)	536.43(.066)	544.30(.052)
FLI	523.41(.089)	528.39(.080)	539.72(.060)
SC	544.25(.052)	545.80(.050)	550.45(.042)
ERC BI	526.18(.084)	525.95(.084)	543.99(.053)
FLI BI	523.15(.089)	528.10(.079)	539.46(.061)
FLI IC	523.25(.089)	525.73(.085)	535.75(.067)
FLI ERC	521.80(.092)	522.81(.090)	539.67(.060)
(ERC BI FLI IC SC)	516.72(.100)	520.44(.094)	535.18(.068)

Several specific models for LFIREDAY constructed using all data.

$SS_{TOT} = 574.40.$

FLI Fuel model C: $SS_{RES} = 523.41$ $R^2 = .089$

$\hat{P} = 1/(1 + \exp(5.97709 - .12093 * FLI))$

Fuel model D: $SS_{RES} = 528.39$ $R^2 = .080$

$\hat{P} = 1/(1 + \exp(6.35198 - .053414 * FLI))$

Fuel model G: $SS_{RES} = 539.72$ $R^2 = .060$

$\hat{P} = 1/(1 + \exp(6.92739 - .126585 * FLI))$

ERC Fuel model D: $SS_{RES} = 526.18$ $R^2 = .084$

$\hat{P} = 1/(1 + \exp(6.60799 - .070648 * ERC))$

FLI, ERC Fuel model C: $SS_{RES} = 521.80$ $R^2 = .092$

$\hat{P} = 1/(1 + \exp(6.0696 - .099883 * FLI - .059213 * ERC))$

A detailed analysis of a logistic model for LFIREDAY using FLI(C) and all data.

FLI(C)	Days	Observed Large firedays	Observed Fraction large firedays	Expected/predicted Raw data Large firedays	Expected/predicted Raw data Fraction large firedays
0	645	1	.0016	1.6	.0025
1-2	726	6	.0083	2.2	.0030
3	705	2	.0028	2.6	.0036
4	996	4	.0040	4.1	.0041
5-10	634	2	.0032	4.0	.0062
11-14	567	4	.0071	6.4	.0114
15-18	604	16	.0265	11.1	.0183
19-26	364	14	.0385	13.5	.0371
27-35	20	2	.1000	1.9	.0972
	5261	51			

Measure of variation is S_1. $SS_{TOT} = 574.4$ Overall $\hat{P} = 51/5261 = .0097$

Model raw data: $\hat{P} = 1/(1 + \exp(5.97709 - .12093 * FLI))$

Summary Statistics

Model	SS_{TOT}	SS_{RES}	SS_{EXP}	R^2
Best $\hat{P}$ each interval	574.4	512.31	62.09	.108
Logistic (raw)	574.4	523.41	50.99	.089

A chi-square statistic computed as illustrated in Chapter 2 gives

$X^2 = 11.10$ d.f. = 9-2 = 7 P-value = .1344

This seems to be a remarkably good model, especially given the small number of large fire days.

Models for FIREDAY based on fire indexes and selected times of the year.

Raw data logistic models were constructed in a few cases for selected days of the year--fire season, before greenup, etc. These results are summarized below and a few of the specific models are also given.

I. Data used: days during fire season 10/1-12/15, 2/15-4/30

SS_{TOT} = 885.28 (using S_1)

Variable	Fuel model	SS_{RES}	R^2
BI	C	825.79	.067
BI	D	834.87	.057
BI	G	825.28	.067

II. Data used: days before greenup only 11/1-4/30

SS_{TOT} = 941.60 (using S_1)

Variable	Fuel model	SS_{RES}	R^2
BI	C	880.69	.065
BI	D	891.91	.053
BI	G	871.13	.075

III. Data used: days when most fires occurred 10/1-3/31

SS_{TOT} = 998.98 (using S_1)

Variables	Fuel model	SS_{RES}	R^2
BI	C	936.37	.063
ERC	C	927.80	.071
FLI	C	938.25	.061
IC	C	936.59	.062
SC	C	966.71	.032
BI ERC FLI IC SC	C	922.80	.076

Several specific logistic models for firedays using data from selected days of the year are given below:

I. Data used: 10/1-12/15, 2/15-4/30 $SS_{TOT} = 885.28$

BI (fuel model C) $SS_{RES} = 825.79$ $R^2 = .067$

$$\hat{P} = 1/(1 + \exp(3.94243 - .066371 * BI))$$

II. Data used: days before greenup 11/1-4/30 $SS_{TOT} = 941.60$

BI (fuel model C) $SS_{RES} = 880.69$ $R^2 = .065$

$$\hat{P} = 1/(1 + \exp(4.35748 - .071267 * BI))$$

BI (fuel model G) $SS_{RES} = 871.13$ $R^2 = .075$

$$\hat{P} = 1/(1 + \exp(4.97114 - .073833 * BI))$$

II. Data used: 10/1-3/31 $SS_{TOT} = 998.98$

BI (fuel model C) $SS_{RES} = 936.37$ $R^2 = .063$

$$\hat{P} = 1/(1 + \exp(4.1265 - .06848 * BI))$$

BI (fuel model C) $SS_{RES} = 927.80$ $R^2 = .071$

$$\hat{P} = 1/(1 + \exp(4.17323 - .162697 * ERC))$$

Models for FIREDAY Based on Weather Variables

Many raw data logistic models for FIREDAY were constructed using one or more weather variables. The following table summarizes these results giving SS_{RES} and R^2 for each model (based on S_1).

SS_{TOT} = 1425.88 (based on S_1). All data were used.

Variable(s)	SS_{RES}	R^2
HUMRISK	1423.46	.002
TEMP	1424.75	.0008
MAXTEMP	1422.79	.002
PRECTIME	1417.95	.006
PRECAMT	1411.07	.010
FUELMOI1	1384.57	.029
FUELMOI2	1401.43	.017
FUELMOI3	1361.31	.045
FUELMOI4	1405.27	.014
MOISWOOD	1359.43	.047
MOISHERB	1355.95	.049
RELHUMID	1371.49	.038
MOISWOOD FUELMOI3	1290.85	.095
MOISHERB FUELMOI3	1289.43	.096
MOISWOOD MOISHERB	1355.87	.049
FUELMOI3 RELHUMID	1347.04	.055
MOISWOOD MOISHERB FUELMOI3	1289.36	.096
MOISWOOD MOISHERB RELHUMID	1323.85	.072
MOISWOOD MOISHERB RELHUMID FUELMOI1	1316.35	.077
MOISWOOD MOISHERB RELHUMID FUELMOI3	1287.38	.097
MOISWOOD MOISHERB RELHUMID FUELMOI1 FUELMOI3	1285.68	.098

Several specific models for LFIREDAY constructed using all data.

$SS_{TOT} = 1425.88$

FUELMOI3: $SS_{RES} = 1361.31$ $R^2 = .045$

$\hat{P} = 1/(1 + \exp(-.692134 + .236375 * \text{FUELMOI3}))$

MOISHERB: $SS_{RES} = 1355.95$ $R^2 = .049$

$\hat{P} = 1/(1 + \exp(2.72373 + .0109416 * \text{MOISHERB}))$

MOISWOOD: $SS_{RES} = 1359.43$ $R^2 = .047$

$\hat{P} = 1/(1 + \exp(1.70068 + .0166901 * \text{MOISWOOD}))$

MOISWOOD, FUELMOI3 $SS_{RES} = 1290.85$ $R^2 = .095$

$\hat{P} = 1/(1 + \exp(-2.4254 + .0186402 * \text{MOISWOOD} + .222464 * \text{FUELMOI3}))$

MOISHERB, FUELMOI3 $SS_{RES} = 1289.43$ $R^2 = .096$

$\hat{P} = 1/(1 + \exp(-1.2426 + .222594 * \text{FUELMOI3} + .0114827 * \text{MOISHERB}))$

Models for FIREDAY Based on Weather Variables and Only 10/1-3/31.

Many raw data logistic models for FIREDAY were constructed using one or more weather variables. The results given here are for models based on data from 6 months (October - March). The table below summarizes these results giving SS_{RES} and R^2.

SS_{TOT} = 998.98 (based on S_1).

Variable(s)	SS_{RES}	R^2
FUELMOI1	957.51	.042
FUELMOI3	911.16	.088
MOISWOOD	985.11	.014
MOISHERB	983.64	.015
RELHUMID	960.29	.039
MOISWOOD MOISHERB	983.26	.016
MOISHERB FUELMOI3	903.71	.095
MOISHERB MOISWOOD FUELMOI3	897.67	.099
MOISHERB MOISWOOD RELHUMID	939.05	.060
MOISHERB MOISWOOD FUELMOI1 FUELMOI3 RELHUMID	885.30	.114

Two specific models for FIREDAY using only months 10/1-3/31

SS_{TOT} = 998.98 (based S_1)

FUELMOI3 SS_{RES} = 911.16 R^2 = .088

$$\hat{P} = 1/(1 + \exp(-2.1909 + .28794 * \text{FUELMOI3}))$$

MOISHERB FUELMOI3 SS_{RES} = 903.71 R^2 = .095

$$\hat{P} = 1/(1 + \exp(-2.1208 + .271696 * \text{FUELMOI3} + .0057952 * \text{MOISHERB}))$$

Chapter 4. Lolo National Forest

Districts: Missoula (03), Ninemile (04), Plains (05), Seeley (06), Superior (07), and Thompson Falls (08).

Weather Station: Missoula (241507)

THE DATA

The fire data used were from the six districts of the Lolo National Forest and weather data from the Missoula Weather Station (241507) were used for all districts. The years used were 1970-85.

WEATHER DATA FILE

Weather data was retrieved from the National Fire Weather Data Library. Variables retrieved are listed in Appendix A. Basically, weather data were available for the months May through October. After the data were retrieved, National Fire Danger Rating System indexes were computed for each day using FIRDAT for fuel models C and G. Occasionally, several days of weather were missing. Weather information for these days was estimated and filled in, using linear interpolation. In this study, days that were in a string of 8 or more missing weather days were not used. Some summary statistics follow:

Missing days	0	1	2	3	6	
Frequency (days)	2451	20	22	3	6	2502
Number of instances	2451	20	11	1	1	

Year	70	71	72	73	74	75	76	77	78	79
Days of useable weather	184	153	151	133	153	107	107	182	184	184

80	81	82	83	84	85	
184	184	153	153	122	168	2502

Month	May	Jun	Jul	Aug	Sep	Oct	
Days of useable weather	401	450	496	496	458	201	2502

Summary Statistics on Weather Variables and Fire Indexes

N=2502

Variable	Mean	Minimum	Maximum	Standard deviation
Temperature	69.3	30	100	13.8
Relative humidity	41.5	2	100	18.5
Windspeed	1.7	0	13	1.7
Maximum temperature	74.2	34	102	12.6
Minimum temperature	40.9	12	68	8.5
Maximum humidity	96.9	15	100	5.6
Minimum humidity	30.3	2	89	13.4
Precipitation time (hours)	.9	0	20	2.1
Precipitation amount	5.1	0	250	16.2
1-hour fuel moisture	8.4	2	32	4.5
10-hour fuel moisture	13.1	2	62	8.3
100-hour fuel moisture	15.2	9	30	2.8
1000-hour fuel moisture	17.8	12	30	3.2
Woody moisture	128.9	70	200	28.0
Herbaceous moisture	118.3	3	250	46.5
Fuel Model C				
IC	12.8	0	94	14.2
SC	3.7	0	37	4.6
ERC	5.0	0	20	4.1
BI	10.5	0	58	9.7
FLI	7.8	0	41	6.8
Fuel Model G				
IC	18.2	0	100	15.2
SC	6.3	0	38	4.4
ERC	29.7	0	60	11.3
BI	31.6	0	92	14.7
FLI	23.4	0	65	9.3

FIRE DATA

Data for fires for Lolo National Forest Districts Missoula, Seeley Lake, Ninemile, Superior, Thompson Falls, and Plains were retrieved from the National Fire Occurrence Library. This file had one case for each fire in each district for years 1970-1985. A case was added to this file for each day in each district that did not have a fire during months when weather data and fire indexes were available. A list of variables taken from the NFODL is given in Appendix A. Summary information on the fires on days with useable weather data follows:

District	Number of fires	Lightning only	Size (acres)	Number of fires	Lightning only
Missoula	448	327	0-.25	1861	1355
Ninemile	507	386	.26 - 9	431	260
Plains	269	180	10 - 99	44	12
Seeley Lake	355	303	100 - 299	14	4
Superior	557	295	300 - 999	9	2
Thompson Falls	225	142	1000 - 4999	1	0
	2361	1633	5000 or more	1	0
				2361	1633

Year	70	71	72	73	74	75	76	77	78	79
Number of fires	191	109	162	338	192	57	114	144	82	299
Lightning only	140	76	122	228	115	34	89	93	38	220

80	81	82	83	84	85	
63	189	63	49	170	139	2361
46	146	35	40	127	84	1633

Month of discovery	May	Jun	Jul	Aug	Sep	Oct	
Number of fires	77	209	692	1109	225	49	2361
Lightning only	35	124	435	906	132	1	1633

Discovery day	Sun	Mon	Tue	Wed	Thur	Fri	Sat	
Number of fires	266	396	296	360	380	349	314	2361
Lightning only	175	295	206	251	266	237	203	1633

Cause	Number of fires
Lightning	1633
Equipment use	82
Smoking	61
Campfire	141
Debris burning	114
Railroad	151
Incendiary	27
Children	57
Miscellaneous	95
	2361

MERGED DATA FILE

The weather and the fire data files were merged. Weather and fire indexes were attached to each case in the fire data file. Cases in the fire data file with no weather/fire index data were deleted. For the analysis reported here, the entire Lolo National Forest was considered as a unit. For example, a fire day means at least one fire discovered in the Lolo National Forest. After this merging of the fire and weather data files, many days have several cases (one for each fire on that day). The cases for each day are collapsed to one case with number of fires and number of large fires on that day computed and added as new variables each day. The following three tables contain information from this data file.

	Number of Days with K Fires												
Number of fires (K)	0	1	2	3	4	5	6	7	8	9	10	≥11	
Number of days with K fires	1605	465	187	87	41	27	17	12	18	12	9	22	2502
Number of days with K lightning fires	1946	301	85	44	33	19	13	10	17	8	6	20	2502

	Number of Days with K Large Fires*			
Number of large fires (K)	0	1	2	
Number of days with K large fires	2440	55	7	2502
Number of days with K large lightning fires	2485	16	1	2502

* 10 acres or more

	All fires	Lightning fires
Number of days	2502	2502
Number of firedays	897	556
Number of large firedays	62	17

Note: In generating the above information, there are two different fire data files used. One contains all fires; the other contains only lightning fires.

An example of the type of information that was generated from the merged data file is the following table.

Number of days with K fires by ERC(G)

Number of fires	0	1	2	3	4	5	6	7	8	9	10	≥11	Total
ERC(G)													
0-10	131*	5	3	1	0	0	0	0	0	0	0	0	140
11-14	102	10	1	0	0	0	0	0	0	0	0	0	113
15-20	242	28	3	3	0	0	0	0	0	1	0	0	277
21-26	313	46	15	9	0	0	1	0	0	1	1	0	386
27-30	246	65	16	11	7	1	2	1	1	0	1	1	352
31-34	235	70	35	10	4	6	2	0	4	4	0	1	371
35-39	196	101	48	24	7	5	5	3	4	1	1	5	400
40-44	74	70	33	14	12	10	5	2	5	0	2	4	231
45-48	40	33	23	5	5	3	1	3	2	3	1	2	121
49-54	22	31	10	7	3	1	1	1	1	2	2	7	88
55-60	4	6	0	3	3	1	0	2	1	0	1	2	23
	1605	465	187	87	41	27	17	12	18	12	9	22	2502

* Numbers in the table are days.

The next several tables give summary information about the NFDRS fire indexes ERC, IC, FLI, BI, and SC for fuel models C and G, firedays and large firedays for all of the data.

Summary statistics relating fire indexes, firedays[1] and large firedays[2]

ERC1(C)	Days	Firedays		Large firedays		ERC2(G)	Days	Firedays		Large firedays	
0	301	50	.166	3	.010	0-10	140	9	.064	0	.000
1	183	38	.208	2	.011	11-14	113	11	.097	0	.000
2	247	78	.316	6	.024	15-20	277	35	.126	2	.007
3	320	70	.219	2	.006	21-26	386	73	.189	4	.010
4	294	97	.330	6	.020	27-30	352	106	.301	7	.020
5	279	122	.437	6	.022	31-34	371	136	.367	14	.038
6-7	313	143	.457	8	.026	35-39	400	204	.510	7	.018
8-10	298	141	.473	11	.037	40-44	231	157	.680	13	.056
11-14	169	93	.550	9	.053	45-48	121	81	.669	6	.050
15-20	98	65	.663	9	.092	49-54	88	66	.750	5	.057
	2502	897		62		55-60	23	19	.826	4	.174
							2502	897		62	

IC1(C)	Days	Firedays		Large firedays		IC2(G)	Days	Firedays		Large firedays	
0	263	51	.194	4	.015	0	234	51	.218	4	.017
1	119	14	.118	0	.000	1-4	183	20	.109	0	.000
2	149	25	.168	1	.007	5-7	216	43	.199	4	.019
3-4	326	86	.264	4	.012	8-11	327	78	.239	2	.006
5-6	244	66	.271	3	.012	12-15	311	106	.341	3	.010
7-10	373	132	.354	7	.019	16-21	408	146	.358	8	.020
11-16	329	121	.368	4	.012	22-28	348	149	.428	13	.037
17-25	315	150	.476	15	.048	29-37	233	144	.618	15	.064
26-34	191	117	.613	13	.068	38-50	140	87	.621	6	.043
35-50	128	84	.656	5	.039	51-60	51	33	.647	2	.039
51-70	41	33	.805	3	.073	61-73	27	22	.815	2	.074
71-94	24	18	.750	3	.125	74-100	24	18	.750	3	.125
	2502	897		62			2502	897		62	

[1] Lolo Forest day with at least one fire
[2] Lolo Forest day with at least one fire 10 acres or more

FLI(C)	Days	Firedays		Large firedays		FLI(G)	Days	Firedays		Large firedays	
0	179	30	.168	0	.000	0-10	110	10	.091	0	.000
1	112	14	.125	0	.000	11-14	234	23	.098	0	.000
2	143	25	.175	0	.000	15-18	424	80	.189	3	.007
3	254	60	.236	3	.012	19-21	417	130	.312	4	.010
4	500	150	.300	12	.024	22-23	316	109	.345	10	.032
5-6	255	100	.392	0	.000	24-27	342	166	.485	17	.050
7-10	328	140	.427	13	.040	28-32	301	156	.518	8	.027
11-14	349	166	.478	15	.043	33-37	155	82	.529	6	.039
15-18	180	101	.561	7	.039	38-44	128	83	.648	10	.078
19-24	130	60	.462	6	.046	45-52	44	36	.818	1	.023
25-30	44	30	.682	3	.068	53-65	31	22	.710	3	.097
31-41	28	21	.750	3	.107						
	2502	897		62			2502	897		62	

BI(C)	Days	Firedays		Large firedays		BI(G)	Days	Firedays		Large firedays	
0	286	53	.185	4	.014	0	126	29	.230	4	.032
1-3	224	38	.170	0	.000	1-15	119	10	.084	0	.000
4	234	57	.244	2	.009	16-22	278	34	.122	0	.000
5	265	74	.279	6	.023	23-27	396	87	.220	2	.005
6-7	347	125	.360	6	.017	28-31	427	138	.323	8	.019
8-12	314	125	.398	10	.032	32-36	390	164	.421	17	.044
13-18	376	175	.465	11	.029	37-41	270	133	.493	9	.033
19-24	224	118	.527	10	.045	42-50	251	142	.566	7	.028
25-34	160	81	.506	7	.044	51-58	134	76	.567	8	.060
35-44	47	31	.660	3	.064	59-70	72	55	.764	4	.056
45-54	24	19	.792	3	.125	71-80	21	16	.762	0	.000
55-58	1	1	1.000	0	.000	81-92	18	13	.722	3	.167
	2502	897		62			2502	897		62	

SC(C)	Days	Firedays		Large firedays	
0	247	46	.186	4	.016
1	947	243	.257	9	.010
2	223	87	.390	5	.022
3-4	405	180	.444	17	.042
5-7	322	154	.478	10	.031
8-10	153	72	.471	5	.033
11-14	108	58	.537	9	.083
15-23	71	40	.563	0	.000
24-37	26	17	.654	3	.115
	2502	897		62	

SC(G)	Days	Firedays		Large firedays	
0	128	29	.227	4	.031
1-2	80	9	.113	0	.000
3	320	58	.181	0	.000
4	430	130	.302	4	.009
5	438	148	.338	16	.037
6	308	135	.438	6	.020
7-8	298	128	.430	11	.037
9-11	230	113	.491	7	.030
12-16	187	95	.508	10	.054
17-24	63	38	.603	1	.016
25-38	20	14	.700	3	.150
	2502	897		62	

Summary Statistics Relating Weather Variables, Firedays and Large Firedays

RELHUMID	Days	Firedays		Large firedays	
2-17	136	92	.677	9	.066
18-23	237	135	.570	11	.046
24-28	300	143	.477	16	.053
29-33	341	140	.411	9	.026
34-39	331	103	.311	7	.021
40-48	381	111	.291	1	.003
49-57	286	67	.234	4	.014
58-68	250	56	.224	1	.004
69-80	128	27	.211	3	.023
81-100	112	23	.205	1	.009
	2502	897		62	

HUMRISK	Days	Firedays		Large firedays	
0	1174	471	.401	31	.026
1	1	0	.000	0	.000
2	184	41	.223	4	.022
3	7	5	.714	0	.000
5	47	7	.149	0	.000
7	545	162	.297	13	.024
9	1	0	.000	0	.000
10	221	70	.317	4	.018
12	210	91	.433	5	.024
13	1	1	1.000	0	.000
15	91	41	.451	4	.044
17	1	1	1.000	0	.000
20	3	1	.333	0	.000
22	5	1	.200	0	.000
33	9	4	.444	1	.111
40	2	1	.500	0	.000
	2502	897		62	

PRECTIME	Days	Firedays		Large firedays	
0	1742	675	.388	55	.032
1	333	103	.309	2	.006
2	135	48	.356	1	.007
3-4	140	41	.293	2	.014
5-7	75	13	.173	1	.013
8-10	57	15	.263	1	.018
11-20	20	2	.100	0	.000
	2502	897		62	

PRECAMT	Days	Firedays		Large firedays	
0	1786	685	.384	55	.031
1-3	186	57	.307	2	.011
4-8	179	53	.296	0	.000
9-16	104	31	.291	0	.000
17-26	102	34	.333	3	.029
27-44	72	20	.278	2	.028
45-80	56	14	.250	0	.000
83-250	17	3	.177	0	.000
	2502	897		62	

FUELMOI1*	Days	Firedays		Large firedays	
2-3	147	92	.626	8	.054
4	228	144	.632	12	.053
5	334	160	.479	20	.060
6	320	126	.394	5	.016
7	268	92	.343	4	.015
8	240	70	.292	2	.008
9	228	62	.272	0	.000
10-11	295	73	.248	4	.014
12-14	220	32	.146	5	.023
15-18	114	24	.211	1	.009
19-25	85	17	.200	1	.012
26-32	23	5	.217	0	.000
	2502	897		62	

FUELMOI2	Days	Firedays		Large firedays	
2-3	69	48	.696	6	.087
4-5	155	94	.607	12	.077
6-7	335	146	.436	9	.027
8-9	430	199	.463	10	.023
10-11	329	110	.334	6	.018
12-13	332	113	.340	8	.024
14-17	356	99	.278	1	.014
18-23	253	48	.190	5	.020
24-30	144	25	.174	1	.007
31-40	54	8	.148	0	.000
41-62	45	7	.156	0	.000
	2502	897		62	

FUELMOI3	Days	Firedays		Large firedays	
9-11	137	93	.679	9	.066
12	235	138	.587	11	.047
13	388	192	.495	10	.026
14	365	160	.438	8	.022
15	313	109	.348	4	.013
16	346	102	.295	13	.038
17	227	54	.238	3	.013
18	192	29	.151	3	.016
19-20	191	14	.073	1	.005
21-23	88	4	.046	0	.000
24-30	20	2	.100	0	.000
	2502	897		62	

FUELMOI4	Days	Firedays		Large firedays	
12	47	39	.830	7	.149
13	112	78	.696	0	.000
14	183	125	.683	13	.071
15	277	172	.621	10	.036
16	369	157	.426	8	.022
17	387	145	.375	13	.034
18	287	63	.220	6	.021
19-20	345	69	.200	3	.009
21-22	233	23	.099	0	.000
23-24	189	22	.116	2	.011
25-30	73	4	.055	0	.000
	2502	897		62	

*FUELMOI1, FUELMOI2, FUELMOI3, FUELMOI4 are the 1-hr, 10-hr, 100-hr, and 1000-hr fuel moistures, respectively.

TEMP	Days	Firedays		Large firedays	
30-45	77	6	.078	1	.013
46-53	243	21	.086	3	.012
54-60	352	47	.134	0	.000
61-67	396	95	.240	6	.015
68-73	389	131	.337	9	.023
74-78	367	175	.477	14	.038
79-83	325	184	.566	9	.028
84-86	144	88	.611	4	.028
87-90	130	93	.715	8	.062
91-100	79	57	.722	8	.101
	2502	897		62	

MAXTEMP	Days	Firedays		Large firedays	
34-50	96	7	.073	1	.010
51-59	275	23	.084	0	.000
60-67	387	53	.137	2	.005
68-74	409	109	.267	10	.024
75-78	310	116	.374	10	.032
79-83	355	165	.465	10	.028
84-87	276	158	.573	9	.033
88-91	194	115	.593	3	.016
92-94	128	94	.734	13	.102
95-102	72	57	.792	4	.056
	2502	897		62	

MOISWOOD	Days	Firedays		Large firedays	
70	96	6	.063	0	.000
71-90	79	55	.696	8	.101
91-102	196	120	.612	5	.026
103-114	357	227	.636	18	.050
115-123	378	164	.434	8	.021
124-132	410	156	.381	13	.032
133-144	355	81	.228	7	.020
145-166	382	66	.173	2	.005
167-182	125	11	.088	1	.008
183-192	53	6	.113	0	.000
193-200	71	5	.070	0	.000
	2502	897		62	

MOISHERB	Days	Firedays		Large firedays	
3-12	71	4	.056	0	.000
13-52	53	8	.151	1	.019
53-75	169	100	.592	10	.059
76-94	382	173	.453	18	.047
95-104	351	159	.453	9	.026
105-114	366	202	.552	10	.027
115-132	355	121	.341	7	.020
133-165	379	83	.219	5	.013
166-193	178	23	.129	1	.006
194-212	96	14	.146	1	.010
213-230	53	4	.076	0	.000
231-250	49	6	.122	0	.000
	2502	897		62	

Models Based on Fire Indexes and Using All Data

Many raw data logistic models for FIREDAY were constructed using one or more of the fire indexes and fuel models C and G. The following table summarizes these results giving SS_{RES} and R^2 for each model.

$SS_{TOT} = 3265.40$

Variable(s)	Fuel Model C	D
ERC	3086.49(.055)*	2766.92(.153)
BI	3100.46(.051)	2979.54(.088)
FLI	3102.05(.050)	2947.79(.097)
IC	3020.52(.075)	3003.88(.081)
SC	3165.65(.031)	3148.67(.036)
BI ERC		2765.07(.153)
BI FLI		2944.37(.098)
ERC FLI		2765.99(.153)
ERC BI FLI		2754.86(.156)
ERC BI FLI IC		2754.83(.156)
All 5 indexes	2976.27(.089)	2751.06(.158)

*SS_{RES} (R^2)

Several specific models are given below. They were constructed using all data:

$$SS_{TOT} = 3265.40$$

ERC (fuel model G) $SS_{RES} = 2766.92$ $R^2 = .153$

$\hat{P} = 1/(1 + \exp(3.63279 - .097708 * ERC))$

IC (fuel model C) $SS_{RES} = 3020.52$ $R^2 = .075$

$\hat{P} = 1/(1 + \exp(1.235 - .049348 * IC))$

ERC, BI (fuel model G) $SS_{RES} = 2765.07$ $R^2 = .153$

$\hat{P} = 1/(1 + \exp(3.63624 - .105407 * ERC + .0072041 * BI))$

FLI (fuel model G) $SS_{RES} = 2947.79$ $R^2 = .097$

$\hat{P} = 1/(1 + \exp(2.67997 - .087459 * FLI))$

In chapters 2 and 3 several logistic models were investigated in detail. The approach used was to group the individual observations into disjointed sets according to their values of the fire index or weather variable in the model. Then observed and expected (found using the logistic model) number of fires were compared as a way of seeing how well the model agreed with the data. Let us call this procedure Method 1. A second procedure, called Method 2 here, will be introduced and illustrated. This method is commonly used to investigate the fit of logistic models.

Method 2 groups the observations according to their estimated P value using the logistic model constructed. The 10 intervals of P values used are [0,.1], (.1,.2], (.3,.4], . . . , (.9,1]. The observed number of fires in each group is compared with the expected number in each group as is done for Method 1. Details on Method 2 are given in Appendix B.

Method 1 is intuitively appealing but becomes very messy when there are two or more variables in the logistic model. With two variables, the observed/expected tables are 2-way for three variables, they are 3-way, etc. On the other hand, when using Method 2, very little extra work is involved when two or more variables are in the logistic model. Several examples of both methods are given in this chapter for both fire index variables and weather variables.

A detailed analysis of a logistic model based on ERC (fuel model G).

SS_{RES} = 2766.92 R^2 = .153 $\hat{P}$ = 1/(1+exp(3.63279 - .097708 * ERC))

Method 1

		Firedays			No firedays	
ERC(G)	Days	O	E	$\hat{P}$	O	E
0-10	140	9	5.8	.041	131	134.2
11-14	113	11	9.3	.082	102	103.7
15-20	277	35	35.3	.128	137	136.7
21-26	386	73	80.3	.208	313	305.7
27-30	352	106	105.5	.300	246	246.5
31-34	371	136	143.8	.388	235	227.2
35-39	400	204	198.2	.496	196	201.8
40-44	231	157	142.2	.616	74	88.8
45-48	121	81	86.3	.713	40	34.7
49-54	88	66	70.6	.802	22	17.4
56-60	23	19	20.3	.884	4	2.7
	2502	897			1605	

x^2=11.17 d.f.=9

P-value = .264

Method 2

		Firedays		No firedays	
$\hat{P}$	Days	O	E	O	E
[0,.1]	253	20	16.1	233	236.9
(.1,.2]	399	60	58.1	339	340.9
(.2,.3]	432	102	107.3	330	324.7
(.3,.4]	456	151	160.9	305	295.1
(.4,.5]	365	166	167.1	199	197.9
(.5,.6]	250	145	138.5	105	111.5
(.6,.7]	149	111	96.2	38	52.8
(.7,.8]	138	92	102.5	46	35.5
(.8,.9]	59	49	49.4	10	9.6
(.9,1]	1	1	.9	0	.1
	2502	897		1605	

X^2=13.98 d.f.=8

P-value = .082

Note: The expected number of fires in an interval is found by summing the $\hat{P}$ values for all observations in that interval.

A detailed analysis of a logistic model based on IC (fuel model C).

SS_{RES} = 3020.52 R^2 = .075 $\hat{P}$ = 1/(1+exp(1.235 - .049348 * IC))

Method 1

		Firedays			No firedays	
IC(C)	Days	O	E	$\hat{P}$	O	E
0	263	51	59.3	.225	212	203.7
1	119	14	27.9	.234	105	91.1
2	149	25	36.2	.243	124	112.8
3-4	326	86	83.7	.257	240	242.3
5-6	244	66	67.4	.276	178	176.6
7-10	373	132	114.4	.307	241	258.6
11-16	329	121	118.9	.362	208	210.1
17-25	315	150	141.9	.450	165	173.1
26-34	191	117	107.2	.561	174	183.8
35-50	128	84	90.0	.703	44	38.0
51-70	41	33	34.9	.852	8	6.1
71-94	24	18	22.7	.945	6	1.3
	2502	897			1605	

x^2=17.22 d.f.=10

P-value = .0070

Method 2

		Firedays		No firedays	
P	Days	O	E	O	E
[0,.1]	0	0	0	0	0
(.1,.2]	0	0	0	0	0
(.2,.3]	1219	284	308.8	935	910.2
(.3,.4]	584	211	197.4	373	386.6
(.4,.5]	315	150	140.9	165	174.1
(.5,.6]	178	108	97.3	70	80.7
(.6,.7]	94	65	61.0	29	33.0
(.7,.8]	57	35	42.6	22	14.4
(.8,.9]	30	25	25.7	5	4.3
(.9,1]	25	19	23.3	6	1.7
	2502	897		1605	

x^2=25.65 d.f.=6

P-value = .0003

A detailed analysis of a logistic model based on ERC (fuel model G) and BI (fuel model G). Only Method 2 will be presented.

$SS_{RES} = 2765.07 \qquad R^2 = .153$

$\hat{P} = 1/(1 + \exp(3.63634 - .105407 * ERC + .0072041 * BI))$

Method 2

		Firedays		No firedays	
$\hat{P}$	Days	O	E	O	E
[0,.1]	267	22	17.2	245	249.8
(.1,.2]	402	59	59.5	343	342.5
(.2,.3]	421	104	105.7	317	315.3
(.3,.4]	403	125	104.5	278	298.5
(.4,.5]	375	172	167.8	203	207.2
(.5,.6]	282	164	154.5	118	127.5
(.6,.7]	162	113	104.9	49	57.1
(.7,.8]	137	93	102.3	44	34.7
(.8,.9]	53	45	44.4	8	8.6
(.9,1]	0	0	0	0	0
	2502	897		1605	

$x^2 = 13.55 \qquad d.f. = 7 \qquad P = .060$

Models Based on Weather Variables and Using All Data

Many raw data logistic models for FIREDAY were constructed using one or more weather variables. The following table summarizes these results giving SS_{RES} and R^2 for each model (based on S_1).

SS_{TOT} = 3265.40 (based on S_1). All data used.

Variable(s)	SS_{RES}	R^2
HUMRISK	3265.09	.000
TEMP	2789.43	.146
MAXTEMP	2750.27	.158
PRECTIME	3237.05	.009
PRECAMT	3252.06	.004
FUELMOI1	3094.23	.052
FUELMOI2	3113.74	.046
FUELMOI3	2919.51	.106
FUELMOI4	2789.02	.146
MOISWOOD	3053.43	.065
MOISHERB	3178.80	.027
RELHUMID	3104.80	.049
TEMP MAXTEMP	2732.61	.163
FUELMOI4 TEMP	2633.51	.194
MAXTEMP FUELMOI3	2734.18	.163
MAXTEMP FUELMOI4	2625.36	.196
FUELMOIS3 FUELMOI4	2740.51	.161
MAXTEMP FUEMOIS3 FUELMOI4	2625.35	.196
MOISWOOD MAXTEMP FUELMOI3 FUELMOI4	2622.58	.197

Several specific models are given below. They were constructed using all the data.

$SS_{TOT} = 3265.40$

MAXTEMP $\quad SS_{RES} = 2750.27 \quad R^2 = .158$

$$\hat{P} = 1/(1 + \exp(7.36301 - .088969 * \text{MAXTEMP}))$$

FUELMOI4 $\quad SS_{RES} = 2789.02 \quad R^2 = .146$

$$\hat{P} = 1/(1 + \exp(-5.5144 + .354037 * \text{FUELMOI4}))$$

FUEL MOI3 $\quad SS_{RES} = 2919.52 \quad R^2 = .106$

$$\hat{P} = 1/(1 + \exp(-4.3347 + .330883 * \text{FUELMOI3}))$$

MAXTEMP, FUELMOI4 $\quad SS_{RES} = 2625.36 \quad R^2 = .196$

$$\hat{P} = 1/(1 + \exp(1.39416 - .061071 * \text{MAXTEMP} + .222904 * \text{FUELMOI4}))$$

Detailed analyses of several models are now presented--most use both Method 1 and Method 2.

A detailed analysis of a logistic model based on MAXTEMP.

SS_{RES} = 2750.27 R^2 = .158

$\hat{P}$ = 1/(1+exp(7.36301 - .088969 * MAXTEMP))

Method 1

		Firedays			No firedays	
MAXTEMP	Days	O	E	$\hat{P}$	O	E
34-50	96	7	2.5	.026	89	93.5
51-59	275	23	21.5	.078	252	253.5
60-67	387	53	59.1	.153	334	327.9
68-74	409	109	106.3	.260	300	302.7
75-78	310	116	112.9	.364	204	207.1
79-83	355	165	163.6	.461	190	191.4
84-87	276	158	154.7	.561	118	121.3
88-91	194	115	125.2	.646	179	168.8
92-94	128	94	91.3	.713	34	36.7
95-102	72	57	57.8	.802	15	14.2
	2502	897			1605	

x^2=11.36 d.f.=8

P-value = .182

Method 2

		Firedays		No firedays	
$\hat{P}$	Days	O	E	O	E
[0,.1]	326	23	22.1	303	303.9
(.1,.2]	432	60	65.2	372	366.8
(.2,.3]	330	82	83.0	248	247.0
(.3,.4]	389	143	139.0	246	250.0
(.4,.5]	292	132	131.9	160	160.1
(.5,.6]	339	191	185.2	148	153.8
(.6,.7]	262	168	171.4	94	90.6
(.7,.8]	119	88	88.5	31	30.5
(.8,.9]	13	10	10.7	3	2.3
(.9,1]	0	0	0	0	0
	2502	897		1605	

x^2=1.59 d.f.=7

P-value = .970

A detailed analysis of a logistic model based on FUELMOI4.

SS_{RES} = 2789.02 R^2 = .146

$\hat{P}$ = 1/(1+exp(-5.5144 + .354037 * FUELMOI4))

Method 1

		Firedays			No firedays		
FUELMOI4	Days	O	E	$\hat{P}$	O	E	
12	47	39	36.7	.780	8	10.3	
13	112	78	79.9	.713	34	32.1	
14	183	125	116.4	.636	58	66.6	x^2=38.83 d.f.=9
15	277	172	152.6	.551	105	124.4	
16	369	157	170.7	.463	212	198.3	
17	387	145	145.7	.377	242	241.3	P-value = .0000
18	287	63	85.4	.298	224	201.6	
19-20	345	69	68.8	.120	276	276.2	
21-22	233	23	25.5	.109	210	207.5	
23-24	189	22	10.8	.057	167	178.2	
25-30	73	4	1.1	.014	69	71.9	
	2502	897			1605		

Method 2

		Firedays		No firedays		
$\hat{P}$	Days	O	E	O	E	
[0,.1]	358	38	22.0	320	336	
(.1,.2]	295	36	44.8	259	350.2	
(.2,.3]	474	107	128.3	367	345.7	
(.3,.4]	387	145	145.7	242	241.3	x^2=30.50 d.f.=6
(.4,.5]	369	157	170.7	212	198.3	
(.5,.6]	277	172	152.6	105	84.4	P-value = .0000
(.6,.7]	183	125	116.4	58	66.6	
(.7,.8]	159	117	116.6	42	42.4	
(.8,.9]	0	0	0	0	0	
(.9,1.0]	0	0	0	0	0	
	2502	897		1605		

A detailed analysis of a logistic model based on FUELMOI3. Only Method 1 is given.

SS_{RES} = 2919.52 R^2 = .106

$\hat{P}$ = 1/(1+exp(-4.3347 + .330883 * FUELMOI3))

Method 1

		Firedays			No firedays		
FUELMOI3	Days	O	E	$\hat{P}$	O	E	
9-11	137	93	100.8	.736	44	36.2	
12	235	138	138.7	.590	97	96.3	
13	388	192	197.2	.508	196	190.8	x^2=23.00 d.f.=9
14	365	160	155.5	.426	205	209.5	
15	313	109	108.9	.348	204	204.1	
16	346	102	95.8	.277	244	250.2	P-value = .0062
17	227	54	49.0	.216	173	168.0	
18	192	29	31.7	.165	163	159.3	
19-20	191	14	20.5	.107	177	170.5	
21-23	88	4	4.4	.050	84	83.6	
24-30	20	2	.2	.010	18	19.8	
	2502	897			1605		

A detailed analysis of a logistic model based on MAXTEMP and FUELMOI4 and only lightning-caused fires. Only Method 2 is given.

SS_{RES} = 2625.36 R^2 = .196

$\hat{P}$ = 1/(1+exp(1.39416 - .061071 * MAXTEMP + .222904 * FUELMOI4))

Method 2

		Firedays		No firedays		
$\hat{P}$	Days	O	E	O	E	
[0,.1]	441	29	24.9	412	416.1	
(.1,.2]	351	44	52.2	307	298.8	
(.2,.3]	341	94	85.3	247	255.7	
(.3,.4]	316	97	110.0	219	206.0	x^2=11.11 d.f.=7
(.4,.5]	290	128	130.7	162	159.3	
(.5,.6]	293	173	161.2	120	131.8	P-value = .134
(.6,.7]	233	152	150.6	81	82.4	
(.7,.8]	170	130	126.8	40	43.2	
(.8,.9]	67	50	55.3	17	11.7	
(.9,1.0]	0	0	0	0	0	
	2502	897		1605		

Lightning Caused Fires

A few of the earlier tables contained some information on lightning-caused fires. The next several pages contain summary statistics and logistic models when only lightning-caused fires are used. FIREDAY, in this case, is defined as a day with one or more lightning-caused fires. Likewise for LFIREDAY. The variables chosen for illustration here are those that were best when all fires were used in building logistic models.

Summary statistics relating fire indexes, firedays and large firedays for lightning-caused fires

ERC(G)	Days	Firedays		Large firedays	
0-10	140	7	.050	0	.000
11-14	113	6	.053	0	.000
15-20	277	21	.076	0	.000
21-26	386	50	.130	1	.003
27-30	352	69	.196	0	.000
31-34	371	84	.226	2	.005
35-39	400	124	.310	1	.003
40-44	231	99	.429	5	.022
45-48	121	50	.413	3	.025
49-54	88	34	.386	3	.034
55-60	23	12	.522	2	.087
	2502	556		17	

BI(G)	Days	Firedays		Large firedays	
0	126	21	.167	1	.008
1-15	119	8	.067	0	.000
16-22	278	26	.094	0	.000
23-27	396	62	.157	0	.000
28-31	427	86	.201	1	.002
32-36	390	103	.264	3	.008
37-41	270	78	.289	2	.007
42-50	251	83	.331	3	.012
51-58	134	43	.321	5	.037
59-70	72	33	.458	1	.014
71-80	21	5	.238	0	.000
81-92	18	8	.444	1	.056
	2502	556		17	

FLI(G)	Days	Firedays		Large firedays	
0-10	110	9	.082	0	.000
11-14	234	16	.068	0	.000
15-18	424	59	.139	0	.000
19-21	417	84	.201	0	.000
22-23	316	69	.218	1	.003
24-27	342	99	.290	4	.012
28-32	301	95	.316	4	.013
33-37	155	51	.329	2	.013
38-44	128	46	.359	5	.039
45-52	44	19	.432	0	.000
53-65	31	9	.290	1	.032
	2502	556		17	

Summary statistics relating weather variables, firedays and large firedays for lightning-caused fires

FUELMOI3	Days	Firedays		Large firedays		FUELMOI4	Days	Firedays		Large firedays	
9-11	137	50	.365	4	.029	12	47	31	.660	5	.106
12	235	77	.328	4	.017	13	112	43	.384	0	.000
13	388	106	.273	4	.010	14	183	79	.432	5	.027
14	365	117	.321	3	.008	15	277	120	.433	5	.018
15	313	85	.272	1	.003	16	369	100	.271	2	.005
16	346	62	.179	0	.000	17	387	83	.215	0	.000
17	227	28	.123	0	.000	18	287	33	.115	0	.000
18	192	18	.094	1	.005	19-20	345	43	.125	0	.000
19-20	191	10	.052	0	.000	21-22	233	8	.034	0	.000
21-23	88	2	.023	0	.000	23-24	189	13	.069	0	.000
24-30	20	1	.050	0	.000	25-30	73	3	.041	0	.000
	2502	556		17			2502	556		17	

TEMP	Days	Firedays		Large firedays		MAXTEMP	Days	Firedays		Large firedays	
30-45	77	1	.013	0	.000	34-50	96	1	.010	0	.000
46-53	243	7	.029	1	.004	51-59	275	9	.033	0	.000
54-60	352	33	.094	0	.000	60-67	387	32	.083	0	.000
61-67	396	61	.154	1	.003	68-74	409	63	.154	1	.002
68-73	389	81	.208	1	.003	75-78	310	75	.242	2	.007
74-78	367	113	.308	3	.008	79-83	355	95	.268	3	.009
79-83	325	112	.345	1	.003	84-87	276	101	.366	1	.004
84-86	144	58	.403	1	.007	88-91	194	80	.412	0	.000
87-90	130	55	.423	4	.031	92-94	128	56	.438	7	.055
91-100	79	35	.443	5	.063	95-102	72	44	.611	3	.042
	2502	556		17			2502	556		17	

Models Based on Fire Indexes and Only Lightning-Caused Fires

Several raw-data logistic models for FIREDAY (a day with one or more lightning-caused fires), were constructed using one or more fire indexes and fuel models C and G. The following table summarizes these results giving SS_{RES} and R^2 for each model.

$SS_{TOT} = 2650.65$

	Fuel model	
Variable(s)	C	G
ERC	2610.26(.015)*	2434.25(.082)
BI	2611.22(.015)	2563.37(.033)
FLI	2611.81(.015)	2554.61(.036)
IC	2598.01(.020)	2602.45(.018)
SC	2625.49(.009)	2627.68(.009)
ERC FLI		2427.39(.084)
All 5 variables	2589.92(.023)	2392.95(.097)

* SS_{RES} (R^2)

Two specific models are:

$SS_{TOT} = 2650.65$

ERC(fuel model G) $SS_{RES} = 2434.25$ $R^2 = .082$

$\hat{P} = 1/(1 + \exp(3.44265 - .068647 * ERC))$

ERC and FLI (fuel model G) $SS_{RES} = 2427.39$ $R^2 = .084$

$\hat{P} = 1/(1 + \exp(3.40543 - .08435 * ERC + .0219558 * FLI))$

Models Based on Weather Variables and Only Lightning-Caused Fires

Several raw data logistic models for FIREDAY (lightning-caused) were constructed using one or more weather variables. The following table summarizes these results giving SS_{RES} and R^2 for each model (based on S_1).

SS_{TOT} = 2650.65 (based on S_1). All data used.

Variable(s)	SS_{RES}	R^2
HUMRISK	2648.73	.001
TEMP	2392.03	.098
MAXTEMP	2313.87	.127
PRECTIME	2649.91	.0003
PRECAMT	2650.59	.00002
FUELMOI1	2618.28	.012
FUELMOI2	2619.64	.012
FUELMOI3	2501.80	.056
FUELMOI4	2359.40	.110
MOISWOOD	2535.04	.044
MOISHERB	2603.96	.018
RELHUMID	2620.95	.011
MAXTEMP FUELMOI4	2248.62	.152
MAXTEMP FUELMOI3 FUELMOI4	2227.87	.160

Several specific models are given here. All models are for lightning-caused fires.

SS_{TOT} = 2650.65

TEMP SS_{RES} = 2392.03 R^2 = .098

$$\hat{P} = 1/(1 + \exp(6.14288 - .067755 * TEMP))$$

MAXTEMP SS_{RES} = 2313.87 R^2 = .127

$$\hat{P} = 1/(1 + \exp(7.66546 - .08269 * MAXTEMP))$$

FUELMOI4 SS_{RES} = 2359.40 R^2 = .110

$$\hat{P} = 1/(1 + \exp(-4.132 + .317672 * FUELMOI4))$$

MAXTEMP, FUELMOI4 SS_{RES} = 2248.62 R^2 = .152

$$\hat{P} = 1/(1 + \exp(2.59898 + .185783 * FUELMOI4 - .057988 * MAXTEMP))$$

Detailed analyses of three of these models are now given.

A detailed analysis of a logistic model based on ERC(G) and only lightning-caused fires..

SS_{RES} = 2434.25 R^2 = .082 $\hat{P}$ = 1/(1+exp(3.44265 - .068647 * ERC))

Method 1

		Firedays			No firedays	
ERC(G)	Days	O	E	$\hat{P}$	O	E
0-10	140	7	6.0	.043	133	134.0
11-14	113	6	7.9	.070	107	105.1
15-20	277	21	26.6	.096	256	250.4
21-26	386	50	53.4	.138	336	332.6
27-30	352	69	64.9	.184	283	287.1
31-34	371	84	85.1	.229	287	285.9
35-39	400	124	115.4	.288	276	284.6
40-44	231	99	84.0	.364	132	147.0
45-48	121	50	53.0	.438	71	68.0
49-54	88	34	46.0	.523	54	42.0
55-60	23	12	14.3	.624	11	8.7
	2502	556			1946	

x^2=15.64 d.f.=9

P-value = .075

Method 2

		Firedays		No firedays	
$\hat{P}$	Days	O	E	O	E
[0,.1]	413	24	29.1	389	383.9
(.1,.2]	761	109	113.3	652	647.7
(.2,.3]	731	184	177.0	547	554.0
(.3,.4]	365	143	124.3	222	240.7
(.4,.5]	153	57	68.5	96	84.5
(.5,.6]	65	32	35.1	33	29.9
(.6,.7]	14	7	8.8	7	5.2
(.7,.8]	0	0	0	0	0
(.8,.9]	0	0	0	0	0
(.9,0]	0	0	0	0	0
	2502	556		1946	

X^2=10.87 d.f.=5

P-value = 0.054

A detailed analysis of a logistic model based on MAXTEMP and only lightning-caused fires.

SS_{RES} = 2313.87 R^2 = .127 $\hat{P}$ = 1/(1+exp(7.66546-.08269 * MAXTEMP))

Method 1

		Firedays			No firedays	
ERC(G)	Days	O	E	$\hat{P}$	O	E
34-50	96	1	1.4	.015	95	94.6
51-59	275	9	11.7	.042	266	263.3
60-67	387	32	31.8	.082	355	355.2
68-74	409	63	58.3	.143	346	350.7
75-78	310	75	64.3	.208	235	245.7
79-83	355	95	97.8	.275	260	257.2
84-87	276	101	98.1	.355	177	179.9
88-91	194	80	84.2	.434	114	109.8
92-94	128	56	64.8	.506	72	63.2
95-102	72	44	44.5	.618	28	27.5
	2502	556			1946	

x^2= 6.50 d.f.=8

P-value = .591

Method 2

		Firedays		No firedays	
$\hat{P}$	Days	O	E	O	E
[0,.1]	711	33	42.1	678	668.9
(.1,.2]	516	91	75.6	425	440.4
(.2,.3]	542	128	132.5	414	409.5
(.3,.4]	339	124	116.6	215	222.4
(.4,.5]	262	113	116.2	149	145.8
(.5,.6]	111	56	59.8	55	51.2
(.6,.7]	14	7	8.8	7	5.2
(.7,.8]	0	0	0	0	0
(.8,.9]	0	0	0	0	0
(.9,0]	0	0	0	0	0
	2502	556		1946	

X^2=8.36 d.f.=5

P-value = .138

A detailed analysis of a logistic model based on MAXTEMP and FUELMOI4 for only lightning-caused fires. Only Method 2 is given.

SS_{RES} = 2248.62 R^2 = .152

$\hat{P}$ = 1/(1+exp(2.59898 + .185783 * FUELMOI4 - .057988 * MAXTEMP))

Method 2

		Firedays		No firedays	
$\hat{P}$	Days	O	E	O	E
[0,.1]	741	27	37.6	714	703.4
(.1,.2]	591	94	88.1	497	502.9
(.2,.3]	421	114	105.2	307	315.8
(.3,.4]	344	133	120.1	211	223.9
(.4,.5]	215	93	95.9	122	119.1
(.5,.6]	132	66	72.2	66	59.8
(.6,.7]	55	27	34.9	28	20.1
(.7,.8]	3	2	2.1	1	.9
(.8,.9]	0	0	0	0	0
(.9,0]	0	0	0	0	0
	2502	556		1946	

X^2=12.97 d.f.=6

P-value = .044

REFERENCES

1. Bradshaw, L. S. 1988. Fire business utility programs--user guide. Systems for Environmental Management and Intermountain Fire Sciences Laboratory.

2. Cox, D. R. 1970. The analysis of binary data. Methuen and Co., LTD.

3. Efron, Bradley. 1978. Regression and ANOVA with zero-one data: Measures of residual variation. J. of the American Statistical Association. 73: 113-121.

4. Hosmer, D. W., and Lemeshow, S. 1980. Goodness of fit tests for the multiple logistic regression model. Communications in Statistics--Theoretical Methods. A9(10): 1043-1069.

5. Landwehr, J. M., Pregibon, D., and Shoemaker, A. C. 1984. Graphical methods for assessing logistic regression models. J. of the American Statistical Association. 79: 61-83.

6. Lemeshow, S., and Hosmer, D. W., Jr. 1982. A review of goodness of fit statistics for use in the development of logistic models. American J. of Epidemiology. 115(1): 92-106.

7. Lemeshow, S., Teres, D., Avrunin, J. S., and Pastides, H. 1988. Predicting the outcome of intensive care unit patients. J. of the American Statistical Association. 83: 348-356.

8. Loftsgaarden, D. O. 1987. The relationship between the National Fire Danger Rating System Indexes and Fire Occurrence--an exploratory study. Cooperative Agreement No. INT-87228. Systems for Environmental Management and Intermountain Fire Sciences Laboratory.

9 Martell, D. L., Otukol, S., and Stocks, B. J. 1987. A logistic model for predicting daily people-caused fire occurrence in Ontario. Can. J. of For. Research. 17: 394-401.

10. Pregibon, D. 1981. Logistic regression diagnostics. The Annals of Statistics, 9(4): 705-724.

11. Steele, B., and Ryan, K. 1987. Goodness of fit in binary logistic regression. Research Work Unit FS-INT-4403, Intermountain Fire Sciences Laboratory.

12. Stukel, Therese A. 1988. Generalized logistic models. J. of the American Statistical Association. 83: 426-431.

APPENDIX A

Variables Obtained from the National Fire Weather Data Library

Station number, year, month, day, relative humidity, Julian date, processing option, state of weather, temperature, wind direction, wind speed, minimum temperature, maximum temperature, minimum relative humidity, maximum relative humidity, precipitation duration, precipitation amount, lightning activity level, human-caused risk, 1-hour fuel moisture, 10-hour fuel moisture, 100-hour fuel moisture, 1000-hour fuel moisture, woody moisture, herbaceous moisture.

Variables Obtained from the National Fire Occurrence Data Library

District, year, month, day, fire size (0 = no fire this day), statistical cause, general cause, specific cause, agency, Forest Service region, AFFIRMS state code, county, administering forest, watershed number, fire ID, time to discovery, time to initial attack, time to first reinforcement, hours to control, slope, aspect, cover, fuel, area burned, class of people.

Variables obtained from FIRDAT using weather data values for each variable below were found for fuel model C, fuel model D, and fuel model G.

Ignition component (IC), spread component (SC), burning index (BI), energy release component (ERC), fire load index (FLI), human-caused fire occurrence index, and lightning-caused fire occurrence index.

APPENDIX B

Methods for Evaluating Logistic Models

Three different techniques were used to evaluate and compare logistic models in this report. In this appendix the procedures are discussed in a little more detail.

I. Efron's R^2

A. Review of ordinary regression

Y = dependent variable x = independent variable

Model: $Y = \beta_0 + \beta_1 x + e$

Data: $(x_1, y_1), (x_2, y_2), \ldots, (x_n, y_n)$

Prediction model: $\hat{Y} = \hat{\beta}_0 + \hat{\beta}_1 X$

Total sum of squares: $SS_{TOT} = \sum_{i=1}^{n} (y_i - \bar{y})^2$

Residual sum of squares: $SS_{RES} = \sum_{i=1}^{n} (y_i - \hat{y}_i)^2$

Explained sum of squares: $SS_{EXP} = SS_{TOT} - SS_{RES}$

Coefficient of determination: $R^2 = SS_{EXP}/SS_{TOT}$

We can think of $\bar{y}$ as being a predictor for Y which doesn't involve the independent variable X. SS_{TOT} measures the variation of the y_i's about $\bar{y}$. If we use $\hat{Y} = \hat{\beta}_0 + \hat{\beta}_1 X$ we predict better and the residual variation is $\sum_{i=1}^{n} (y_i - \hat{y}_i)^2$ which is smaller than SS_{TOT}. The difference is SS_{EXP} which is the part of SS_{TOT} explained by the model $\hat{Y}$ with X in it. R^2 expresses this as a fraction of SS_{TOT}, i.e., $0 \leq R^2 \leq 1$.

B. Logistic regression and Efron's R^2.

Logistic regression models were introduced on page 22 of this report. Here the y_i's are all 0's or 1's, a 1 being a fireday. In this case $\bar{y} = \bar{p}$ which is the overall fraction of firedays among the n days. Also, $\hat{Y}$ is now $\hat{P}$ where $\hat{P}$ is an estimate of the probability of a fireday as a function of the independent variable or variables. Efron (1978) has introduced ways of measuring variation in this case that are analogous to the ordinary regression situation. Two of these, S_1 and S_2 are introduced here. S_1 was chosen as the preferred one and used throughout this report.

Here $y = 0$ or 1 and $0 \leq \Pi \leq 1$.

$$S_1(y, \Pi) = \begin{cases} -2 \ln \Pi & y = 1 \\ -2 \ln(1-\Pi) & y = 0 \end{cases}$$

$$S_2(y, \Pi) = (y - \Pi)^2.$$

We illustrate both of these with a few numerical examples.

Π	y	$S_1(y,\Pi)$	$S_2(y,\Pi)$
.1	0	$-2\ln(.9) = .21$	$(0-.1)^2=.01$
.1	1	$-2\ln(.1) = 4.61$	$(1-.1)^2=.81$
.4	0	$-2\ln(.6) = 1.02$	$(0-.4)^2=.16$
.4	1	$-2\ln(.4) = 1.83$	$(1-.4)^2=.36$
.5	0	$-2\ln(.5) = 1.39$	$(0-.5)^2=.25$
.5	1	$-2\ln(.5) = 1.39$	$(1-.5)^2=.25$
.75	0	$-2\ln(.25) = 2.77$	$(0-.75)^2=.56$
.75	1	$-2\ln(.75) = .58$	$(1-.75)^2=.06$
.95	0	$-2\ln(.05) = 5.99$	$(0-.95)^2=.9025$
.95	1	$-2\ln(.95) = .10$	$(1-.95)^2=.0005$

Both S_1 and S_2 behave as we would expect.

For logistic regression $y_1, y_2, \ldots, y_n$ are 0's and 1's and for each y_i we have a predicted value for a fireday giving $\hat{p}_1, \hat{p}_2, \ldots, \hat{p}_n$. The sums of squares are then defined as follows:

$$SS_{TOT} = \sum_{i=1}^{n} S_1(y_i, \bar{p}) \qquad \left(\text{or } \sum_{i=1}^{n} S_2(y_i, \bar{p})\right)$$

$$SS_{RES} = \sum_{i=1}^{n} S_1(y_i, \hat{p}_i) \qquad \left(\text{or } \sum_{i=1}^{n} S_2(y_i, \hat{p}_i)\right)$$

$$SS_{EXP} = SS_{TOT} - SS_{RES}$$

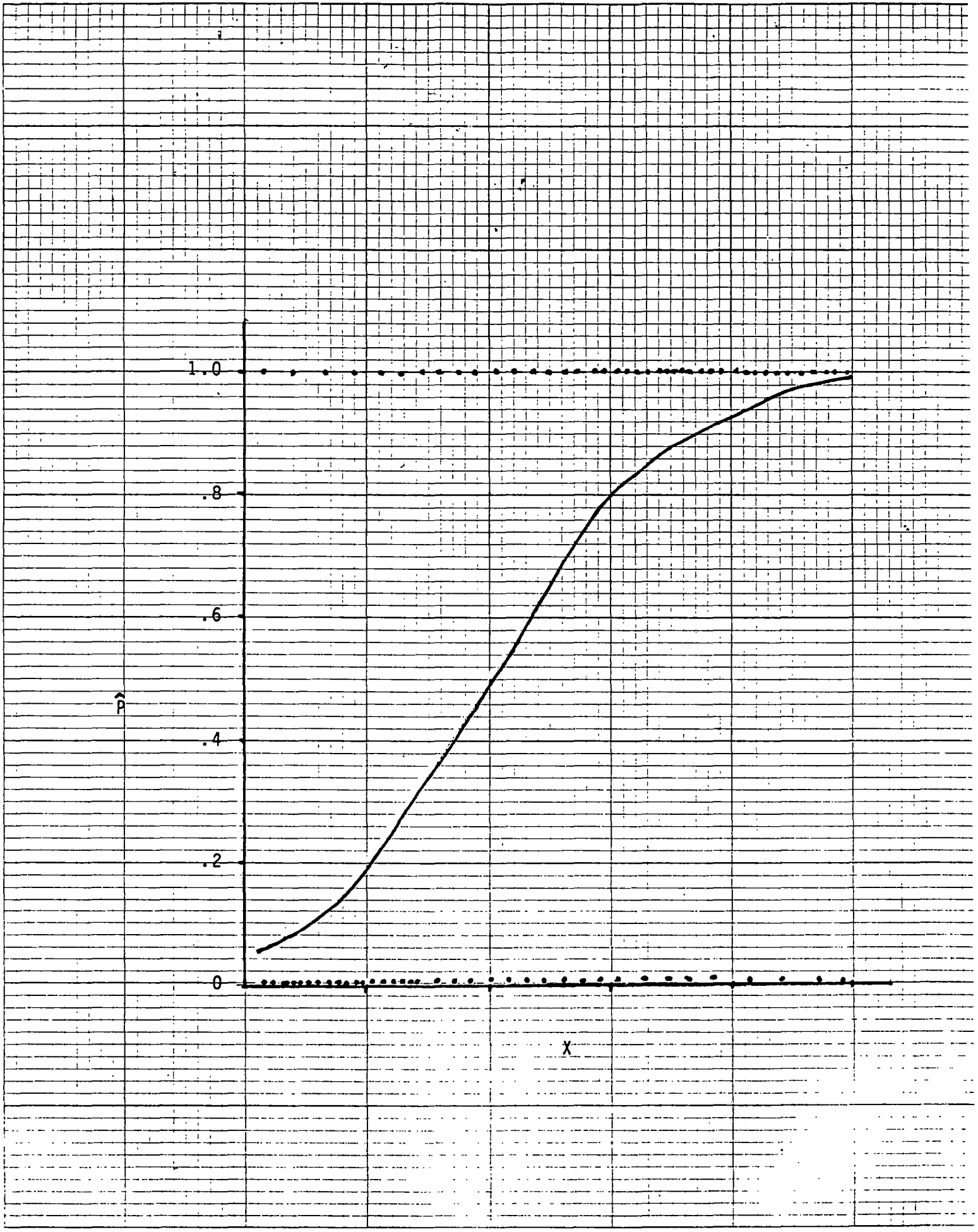
The logistic model is $\hat{P} = 1/(1 + \exp(\hat{\beta}_0 + \hat{\beta}_1 X))$ where $\hat{\beta}_0$ and $\hat{\beta}_1$ are the maximum likelihood estimates for β_0 and β_1. Since Y is a binomial random variable, it turns out that $SS_{RES} = \sum_{i=1}^{n} S_1(y_i, \hat{p}_i)$ is -2 times the natural log of the likelihood ratio and thus $\hat{\beta}_0$ and $\hat{\beta}_1$ are chosen to minimize SS_{RES} in this case. This is the reason we chose to use S_1 in this report.

This last fact also means that SS_{RES} has an approximate chi-square distribution. This can be used in making tests. For example, suppose we construct a logistic model with one independent variable and compute SS_{RES}. Then we construct a second logistic model with three independent variables and compute a new SS_{RES} which is, of course, smaller. The difference in these two sums of squares has an approximate chi-square distribution with two degrees of freedom which can be used to test whether the second model is a significant improvement over the first model or not.

Using SS_{TOT} and SS_{EXP} as defined here, we again define R^2 as SS_{EXP}/SS_{TOT}. If one has constructed two models for the same set of data, one would prefer the one with the larger R^2.

The following figure shows a typical situation of the type we are considering here. A logistic model is shown along with a set of y_i's which are all either 0 or 1. For the small values of X, there are many 0's and few 1's and the reverse is true for large X values. For middle values of X, there is a much more equal distribution of 0's and 1's. SS_{RES} measures variation of the y_i's about the logistic curve $\hat{P}$. Clearly, 0's and 1's are both a long ways from this curve for middle values of X. For small X values, the 0's are near the curve and most of the observations there are 0's. For large values of X, most of the observations are 1's which are near the curve. It is easy to see, then, that the particular data set one has in hand has a big influence on the R^2 one obtains. If the observations are concentrated at small and large X values, SS_{RES} will be small and R^2 large, whereas if many observations are concentrated near the middle values of X, SS_{RES} will be larger and R^2 smaller. This makes it difficult to compare R^2's for models constructed from different sets of data.

Efron has given us a way to do some things analogous to what we are used to doing with ordinary regression. However, it is clear that variation in the logistic situation is not the same variation in the ordinary regression situation.


1.0
.8
.6
$\hat{P}$
.4
.2
0
X

II. Chi-Square Like Methods

Two other methods were illustrated for examining how well constructed logistic models fit the data. Typical examples of these two methods are found on page 81 in the main body of this report.

Method 1 groups the days according to values of a predictor variable or variables recorded for each day. In the example referred to above, the grouping was done using values of ERC(G). Once the grouping is done, the observed number of firedays and no firedays in each group are compared with predicted numbers for these same quantities. The expected (predicted) numbers for a particular group are found by using the logistic model to get a $\hat{P}$ for the group. This $\hat{P}$ is multiplied by the number of days in the group to get the expected number of firedays. The expected number of firedays in the group is then found by subtraction.

For each group, an approximate chi-square random variable with 1 degree of freedom is calculated as follows:

$$\frac{(\text{Obs. firedays}-\text{exp. firedays})^2}{\text{exp. firedays}} + \frac{(\text{Obs. no firedays} - \text{exp. no firedays})^2}{\text{exp. no firedays}}$$

If one sums these chi-squares for all groups, you ordinarily expect to get another chi-square random variable. However, because we are using the same $\hat{P}$ to compute expected values in each group, the chi-squares we are summing are not independent. Nevertheless, there is some evidence that a chi-square approximation for this sum is not too bad. If there is one variable in the logistic model, then the degrees of freedom are approximately the number of groups minus 2.

This method is reasonably useful with one independent variable. With two independent variables, the groups come from a 2-way table with many cells and this method then becomes very cumbersome and not nearly as useful. With three or more independent variables, this method is not useful at all. This is unfortunate as we need to be able to evaluate logistic models with several independent variables.

Method 2, illustrated on page 81, also groups the days. This time a $\hat{P}$ value is computed for each individual day using the logistic model. The days are then divided into 10 groups on the basis of $\hat{P}$ values. Sometimes there are no days, with the large $\hat{P}$ values resulting in fewer than 10 groups. It is just as easy to do the grouping required here with several independent variables as it is with one independent variable. Thus this method does not have the problem that the first method discussed here has.

Again, for this method we compare observed and expected firedays and observed and expected no-fire days for each group. Here the expected number of firedays in a group is found by summing the $\hat{P}$'s for all days in the group and the expected number of no firedays is found by subtraction. A chi-square-like statistic can be computed in the same way as it was for Method 1. There is some simulation evidence that this statistic will have an approximate chi-square distribution. When there is one independent variable in the logistic model, two parameters are estimated and the chi-square statistic has degrees of freedom equal to the number of groups minus 2. See Hosmer and Lemeshow (1980) for more information.

Even though there are are problems with the distributions of the test statistics for both of the methods discussed here, they both seem to be fairly useful for looking at logistic models. Examining the tables of observed and expected values one constructs in either case can give one a pretty good feel for how good a particular logistic model is.

III. Other Procedures

The problem of evaluating logistic models is of interest to many people and currently much work is being done on this problem by many people in statistics. Sometimes each new issue of a statistics journal brings another paper on this subject. It is a difficult problem and is by no means solved as yet. We reference here some of the more interesting papers in this area that have appeared recently. Efron (1978, Hosmer and Lemeshow (1980), Landwehr, Pregibon, and Shoemaker (1984), Lemeshow and Hosmer (1982), Lemeshow, Teres, Avrunin and Pastides (1988), and Pregibon (1981).

APPENDIX C

List of Programs and Data Files

Mississippi (Black Creek Station)

1.	MISS_FILLED_WX	Raw data file of weather/indexes data.
2.	MISS_FILLED_FIRES	Raw data file of fires data.
3.	WEATHR.SAS	Creates SAS file WEATHR.SSD using data file MISS_FILLED_WX.
4.	WEATHR.SSD	Weather/indexes SAS data file created by WEATHR.SAS.
5.	WEATHR2.SAS	Uses WEATHR.SSD and does summary statistics on all weather/indexes variables for the Black Creek Station. Days with weather missing for 8 or more consecutive days are deleted.
6.	FIRE.SAS	Creates SAS file FIRE.SSD using data file MISS_FILLED_FIRES.
7.	FIRE.SSD	Fire SAS data file created by FIRE.SAS.
8.	FIRE2.SAS	Does checking and summary statistics for fires from three districts combined (Biloxi, Black Creek, and Chickasawhay).
9.	MERGE.SAS	Attaches weather/index variables from WEATHR.SSD creating a merged SAS file MERGE.SSD. Each fire gets its weather/index variables from the Black Creek Station.
10.	MERGE.SSD	SAS file created by MERGE.SAS.
11.	MERGE2.SAS	Uses MERGE.SSD and creates a smaller SAS file MERGE2.SSD by dropping some variables and all fires without weather data.

12.	MERGE2.SSD	SAS file created by MERGE2.SAS.
13.	ANAL1.SAS	Uses MERGE2.SSD to create ANAL1.SSD, a SAS file. All data from one day is collapsed to one observation and new variables FIRES, LARFIRES, FIREDAY, LFIREDAY are added to the file.
14.	ANAL1.SSD	SAS data file created by ANAL1.SAS from MERGE2.SSD.
15.	ANAL2.SAS	Uses ANAL1.SSD and does frequency counts for the fire indexes and weather variables.
16.	WEATHR3.SAS	Three programs by this name used to find bad data in weather file.
17.	FIRE2FIN.SAS	Uses MERGE2.SSD and runs frequencies on fire variables for fires that have weather attached.
18.	FIRE2A.SAS	Uses MERGE2.SSD and runs frequencies on fire variables for fires that have weather attached and only for months Jan-April, Oct-Dec.
19.	FIRE2B.SAS	Same as FIRE2FIN.SAS (17 above) except only fires with cause-incendiary are used.
20.	TEST3.SAS	Uses ANAL1.SSD and does crosstabs of fire indexes with FIRES, LARFIRES, FIREDAY and LFIREDAY.
21.	TEST3W.SAS	Uses ANAL1.SSD and does crosstabs of weather variables with FIRES, LARFIRES, FIREDAY and LFIREDAY.
22.	ANAL1I.SAS	This program creates SAS file ANAL1I.SSD which is the same as ANAL1.SSD except only fires with cause-incendiary are used.

23. ANAL1I.SSD — SAS file created by NAL1.SAS.

24. TEST3I.SAS — Uses ANAL1I.SSD (only fires with cause-incendiary), and does crosstabs of fire indexes with FIRES, LARFIRES, FIREDAY and LFIREDAY.

25. TEST3A.SAS — Uses ANAL1.SSD and does a couple of 3-way crosstabs for two fire indexes with FIREDAY and LFIREDAY.

26. TEST3E.SAS — Uses ANAL1.SSD and does a couple of 3-way crosstabs for two weather variables with FIREDAY and LFIREDAY.

27. TEST3B.SAS — Uses ANAL1.SSD and selects months Jan-April, Oct-Dec. Does crosstabs of ERC2(D) by FIRES, FIREDAY, LARFIRES and LFIREDAY.

28. TEST3C.SAS — Uses ANAL1.SSD and selects only the fire season. (2/15-4/30 and 10/1-12/15). Does crosstabs of ERC2(D) by FIRES, FIREDAY, LARFIRES, and LFIREDAY.

29. LOGFI1.SAS
30. LOGFI5.SAS
31. LOGERCSQ.SAS — Programs 29, 30, 31 use all data and construct logistic models for FIREDAY using as independent variables the fire indexes.

32. LOGFI2.SAS — Uses ANAL1.SSD and selects months Jan-April, Oct-Dec. Constructs logistic models for FIREDAY based on fire indexes.

33. LGGR5.SAS — Uses ANAL1.SSD and constructs a bivariate grouped logistic model for FIREDAY using ERC2(D) and BI2(D).

34. LOGFI3C.SAS
35. LOGFI3.SAS

Programs 34, 35 use ANALI.SSD and select days 2/15-4/30 and 10/1-12/15 (fire season). Logistic models for FIREDAY using fire indexes are constructed.

36. LOGFI4A.SAS
37. LOGFI6A.SAS
38. LOGFI7A.SAS

Programs 36, 37, 38 use ANAL1I.SSD which contains only fires with cause-incendiary. A number of logistic models for FIREDAY are constructed using all data and fire indexes.

39. LOGFI4.SAS
40. LOGFI6.SAS
41. LOGFI7.SAS

Programs 39, 40, 41 use ANAL1I.SSD, only fires with cause-incendiary and months Jan-April and Oct-Dec. A number of logistic models for FIREDAY are constructed using fire indexes.

42. LOGWEA3.SAS
43. LOGWEA4.SAS

Programs 42, 43 use ANAL1.SSD and all months. A number of logistic models for FIREDAY based on weather variables are constructed.

APPENDIX D

List of Programs and Data Files

Mississippi (Bude Station)

1.	MISS2_FILLED_WX	Raw data file of weather/indexes data.
2.	MISS2_FILLED_FIRES	Raw data file of fires data.
3.	WEATHR.SAS	Creates SAS file WEATHR.SSD using MISS2-FILLED_WX.
4.	WEATHR.SSD	SAS file created using WEATHR.SAS.
5.	WEATHR2.SAS	Uses WEATHR.SSD and gets summary statistics for the weather variables and fire indexes.
6.	FIRE.SAS	Creates SAS file FIRE.SSD using data file MISS2_FILLED_FIRES.
7.	FIRE.SSD	SAS file created by FIRE.SAS.
8.	FIRE2.SAS	Does checking and summary statistics for fires from two districts combined (Bude and Homochitto).
9.	MERGE.SAS	Attaches weather index variables from WEATHR.SSD to fires in FIRE.SSD creating MERGE.SSD. Each fire gets its weather/index variables from the Bude station.
10.	MERGE.SSD	SAS file created by MERGE.SAS.
11.	MERGE2.SAS	Uses MERGE.SSD and creates a smaller SAS file MERGE2.SSD by dropping some variables and all fires without weather data.
12.	MERGE2.SSD	SAS file created by MERGE2.SAS.

13.	ANAL1.SAS	Uses MERGE2.SSD to create ANAL1.SSD, an SAS file. All data from one day is collapsed to one observation and new variables FIRES, LARFIRES, FIREDAY, and LFIREDAY are added to the file.
14.	ANAL1.SSD	SAS data file created by ANA1.SAS from MERGE2.SSD.
15.	ANAL2.SAS	Uses ANAL1.SSD and does frequency counts for the fire indexes and a few weather variables.
16.	ANAL2A.SAS	Uses ANAL1.SSD and does frequency counts for the weather variables.
17.	FIRE2FIN.SAS	Uses MERGE2.SSD and does frequencies for the fires that had weather data.
18.	FIRE2A.SAS	Uses MERGE2.SSD and does frequencies for the fires with weather data in months Jan-Mar and Oct-Dec.
19.	FIRE2B.SAS	Uses MERGE2.SSD and does frequencies for fires with weather data in all months but only fires with cause-incendiary.
20.	TEST3.SAS	Uses ANAL1.SSD and does crosstabs of FIRES, LARFIRES, FIREDAY and LFIREDAY by selected fire indexes.
21.	TEST3A.SAS	Same as 20 for different indexes.
22.	TEST3W.SAS	Uses ANAL1.SSD and does crosstabs of FIRES, LARFIRES, FIREDAY, LFIREDAY by weather variables.
23.	FLIGROUP.SAS	Use grouped data to construct a logistic model for FIREDAY based on FLI(C).

24.	LOGERC.SAS	Programs 24-28 use ANALI.SSD and construct
25.	LOGBI.SAS	logistic models for FIREDAY and LFIREDAY based
26.	LOGIC.SAS	on ERC, BI, IC, FLI and SC for three fuel models
27.	LOGFLI.SAS	C, D, and G,respectively. Only 1 variable models.
28.	LOGSC.SAS	
29.	LOG2VFLI.SAS	Programs 29-32 use ANAL1.SSD and construct
30.	LOG2VFLIA.SAS	logistic models for FIREDAY and LFIREDAY based
31.	LOGERCBI.SAS	on two fire indexes and three different fuel
32.	LOG2VAR.SAS	models for a variety of two variable models.
33.	LOGEIB.SAS	Programs 33-35 use ANAL1.SSD and construct
34.	LOGFOUR.SAS	several logistic models for FIREDAY and
35.	LOG5VAR.SAS	LFIREDAY based on 3, 4, or 5 indexes and 3 fuel models.
36.	LOGBIFS.SAS	Programs 36-38 use ANAL1.SSD and construct
37.	LOGBIGU.SAS	several logistic models for FIREDAY and LFIREDAY
38.	LOGFIRES.SAS	based on fire indexes. Only selected months are used (e.g., fire season, before greenup, etc.)
39.	LLOGWEA.SAS	Programs 39-45 use ANAL1.SSD and construct
40.	LLOGWEA2.SAS	several logistic models for FIREDAY based on
41.	LLOGWEA3.SAS	one or more weather variables.
42.	LLOGWEA4.SAS	
43.	LLOGWEA8.SAS	
44.	LLOGWEA9.SAS	
45.	LLOGWEA10.SAS	

46. LLOGWEA11.SAS Uses ANAL1.SSD and only months Jan-Mar and Oct-Dec. Several logistic models for FIREDAY based on one or more weather variables are constructed.

APPENDIX E

List of Programs and Data Files

Lolo National Forest

1.	LOLO_FILLED_WX	Raw data file of weather/indexes data.
2.	LOLO_FILLED_FIRES	Raw data file of fires data.
3.	WEATHR.SAS	Creates SAS file WEATHR.SSD using data file LOLO_FILLED_WX.
4.	WEATHR.SSD	Weather/indexes SAS data file created by WEATHR.SAS.
5.	WEATHR2.SAS	Uses WEATHR.SSD and does summary statistics on all weather/indexes variables for STATNO=241507 the Missoula weather station.
6.	FIRE.SAS	Creates SAS file FIRE.SSD using data file LOLO_FILLED_FIRES.
7.	FIRE.SSD	Fire SAS data file created by FIRE.SAS.
8.	FIRE2.SAS	Mainly does some checking on fire data. More interesting fire summaries come later when fires from all Districts are combined for Lolo National Forest days.
9.	MERGE.SAS	Attaches weather/index variables from WEATHR.SSD to each fire in FIRE.SSD creating a merged SAS file MERGE.SSD. In this merged data file, each fire gets its weather/index variables from its own weather station.
10.	MERGE.SSD	SAS data file created by MERGE.SAS

11.	MERGE2.SAS	Uses MERGE.SSD and creates a smaller SAS file MERGE2.SSD by dropping some variables and fires without weather data.
12.	MERGE2.SSD	SAS data file created by MERGE2.SAS.
13.	ANAL1.SAS	Creates ANAL1.SSD, a SAS data file, from MERGE2.SSD by collapsing all fires for one day to one case. New variables FIREDAY, LFIREDAY, FIRES, and LARFIRES are created. All information is by separate district.
14.	ANAL1.SSD	SAS data file created by ANAL1.SAS.
15.	MERGELF.SAS	Creates SAS file MERGELF.SSD from WEATHR.SSD and FIRE.SSD, a merged SAS file. Only one weather station (STATNO = 241507, Missoula) is used to attach weather/indexes to the fires.
16.	MERGELF.SSD	SAS data file created by MERGELF.SAS.
17.	MERGELF2.SAS	Creates a smaller SAS data file, MERGELF2.SSD, from MERGELF.SSD by dropping a few variables and all fires with no weather data attached.
18.	MERGELF2.SSD	SAS data file created by MERGELF2.SAS.
19.	ANALLF1.SAS	Use MERGELF2.SSD to create a smaller SAS data file ANALLF1.SSD by collapsing all fires for one day to one case. These are Lolo National Forest days. New variables FIREDAY, LFIREDAY, FIRES, and LARFIRES are created.
20.	ANALLF1.SSD	SAS data file created by ANALLF1.SAS.

21.	ANALLF2.SAS	Uses ANALLF2.SSD to do frequency counts on all variables to determine intervals when data is grouped.
22.	FIRE2FIN.SAS	Uses fires from MERGELF2.SSD and does some frequencies for these fires. All of these fires have weather/indexes attached and these weather/indexes all come from STATNO=241507 (Missoula).
23.	TEST3F.SAS	Uses ANALLF1.SSD and does crosstabs of fire index variables with FIRES, LARFIRES, FIREDAY, LFIREDAY. These are Lolo National Forest days.
24.	TEST3W.SAS	Uses ANALLF1.SSD and does crosstabs of weather variables with FIRES, LARFIRES, FIREDAY, LFIREDAY. These are Lolo National Forest days.
25.	LOGFI1.SAS	These two programs use ANALLF1.SSD and run a variety of logistic models for FIREDAY based on one or more fire indexes. Lolo National Forest days models.
26.	LOGFI2.SAS	
27.	LOGWEA1.SAS	These two programs use ANALLF1.SSD and run a variety of logistic models for FIREDAY based on one or more weather variables. Lolo National Forest days models.
28.	LOGWEA2.SAS	

29.	ANLFLIG1.SAS	Uses MERGELF2.SSD and only lightning-caused fires. Creates ANLFLIG1.SSD by collapsing all fires for one day to one case. These are Lolo National Forest days. New variables created: FIREDAY, LFIREDAY, FIRES, LARFIRES.
30.	ANLFLIG1.SSD	SAS data file created by ANLFLIG1.SAS.
31.	ANLFLIG2.SAS	Uses ANLFLIG1.SSD and obtains frequencies for FIRES, LARFIRES, FIREDAY, LFIREDAY.
32.	FIRE2LIFIN.SAS	Uses MERGELF2.SSD. Generates frequency information on lightning-caused fires from this data set. Lolo National Forest days.
33.	TESTLIG3F.SAS	Uses ANLFLIG1.SSD and gets crosstabs of three fire indexes with FIRES, LARFIRES, FIREDAY, LFIREDAY. Lolo National Forest days. Lightning-caused fires.
34.	TESTLIG3W.SAS	Uses ANLFLIG1.SSD and gets crosstabs of four weather variables with FIRES, LARFIRES, FIREDAY, LFIREDAY. Lolo National Forest days. Lightning-caused fires.
35.	LOGLIFI1.SAS	These two programs use ANLFLIG1.SSD and run a variety of logistic models for FIREDAY based on one or more fire indexes. Lolo National Forest days and lightning-caused fires.
36.	LOGLIFI2.SAS	

37. LOGLIWEA1.SAS
38. LOGLIWEA2.SAS

These two programs use ANLFLIG1.SSD and run a variety of logistic models for FIREDAY based on one or more weather variables. Lolo National Forest days and lightning-caused fires.

39. FIT1.SAS
40. FIT2.SAS

These two programs use ANALLF1.SSD and do LEMESHOW (JASA June 88) type tests of fit using all fires and Lolo National Forest days.

41. FIT3.SAS

This program uses ANLFLIG1.SSD and does LEMESHOW (JASA June 88) type tests of fit using Lolo National Forest days and lightning-caused fires.